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Tariffs and Politics: Evidence from Trump's Trade Wars

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Trade Wars and Politics: Evidence from Trump's Trade Wars*

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Abstract

We use the recent trade escalation between the US and its trade partners to study whether retaliatory tariffs are politically targeted. We find comprehensive evidence using individual- and aggregate voting data suggesting that retaliation is carefully targeted to hurt Trump. We develop a simulation approach to construct counterfactual retaliation responses allowing us to both quantify the extent of political targeting, while also studying potential trade-offs. China, appears to put a large weight on achieving maximal political targeting. The EU seems successful in maximizing political targeting, while at the same time minimizing the potential damage to its economy.

Keywords: trade war, tariff, targeting, political economy, elections, populism

JEL Codes: F13, F14, F16, F55, D72

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1 Introduction

“Trade wars are good, and easy to win.”, based on this assertion President Donald Trump announced on March 1, 2018 that the US would impose a 25% tariff on steel and a 10% tariff on aluminium imports. Initially exempt, Canada, Mexico, and the EU became subject to the steel and aluminium tariffs from May 31, 2018. Additionally, the Trump administration set a tariff of 25% on 818 categories of goods imported from China worth \$50 billion on July 6. Despite Trump’s claims, the dispute involving China, the European Union (EU), Canada and Mexico escalated with reciprocal tariffs being imposed on imports from the US. Anecdotal evidence suggests that these retaliatory tariffs were chosen in a way to maximize political pressure on the US ([Chan and Smale, 2018](#)). The EU, for example imposed tariffs on iconic American brands like Harley-Davidson motorbikes, which are produced in Wisconsin the home state of then Speaker of the House Paul Ryan. While suggestive, we so far know little about how countries design their retaliatory tariffs, as few trade disputes reach a stage of escalation in which threatened tariffs are actually imposed or retaliation measures are triggered. This paper fills this gap by investigating the degree to which retaliation by the US trade partners was politically targeted. Further, we evaluate the extent to which countries and trading blocks optimize trade-offs when designing a retaliation response.

In the first part of the paper, we ask whether the retaliatory tariffs are designed to target Trump’s voter base. We document that retaliatory tariffs are distinctly targeted towards areas that supported Trump in the 2016 election. To assess the degree of political targeting, we construct a county-specific retaliation exposure measure similar to [Autor et al. \(2013\)](#) using data on US exports. Based on this ex-

posure measure, we find that retaliatory tariffs target areas that swung to Trump in the 2016 presidential election. In contrast, areas that swung behind other Republican candidates in the House or Senate elections held on the same day were not target of retaliatory tariffs. Our estimates suggest that areas most exposed to retaliatory tariffs from China exhibited an up to 5 percentage point stronger swing to Trump relative to the performance of the 2012 Republican candidate. Using individual-level opinion polling data, we show that even among self-identifying Republicans retaliation appears to be distinctly targeted towards areas in which Republicans favored Donald Trump over other Republican contestants for the 2016 presidential nomination. Further, we document that the degree of political targeting appears to pick up a distinct shift in geographic patterns in Republican party affiliation – but only after Donald Trump entered the 2016 Presidential race in 2015. Lastly, we also draw on data from an individual-level panel dataset, with further corroborates these findings.

In the second part, we investigate both the feasibility of political targeting and study the extent to which countries face trade-offs in their retaliation design, in particular, the harm retaliation may afford on their own economy. To do so, we propose a novel simulation approach. This simulation approach aims to approximate the choice set that each retaliating country faces. The approach works by drawing alternative feasible retaliation baskets that could have been chosen and would produce a similar-sized retaliation response. For each of the simulated alternative baskets, we then construct our implied county-level retaliation exposure measure. Further, we use the *revealed comparative advantage* index introduced by Balassa (1965) along with estimated trade-elasticities to measure the likely effec-

tiveness and also proxy for the likely economic pressure that a specific retaliation response implies for a retaliating trading bloc's own economy. In a similar spirit, we construct a measure capturing the extent to which the US is a dominant supplier of specific goods in a retaliation response. These measures allow us to evaluate whether there exist tangible trade-offs between higher degrees of political targeting and likely domestic economic harm due to retaliation.

In our analysis, we compare the actually chosen retaliation response relative to the counterfactual baskets. We observe that while both China and the EU are able to achieve a high degree of political targeting, only the EU appears to specifically aim to mitigate the harm to its own economy. In contrast, China seems not concerned about retaliating against goods for which the US has a high revealed comparative advantage or is its main supplier. It is particularly remarkable that it would have been possible for China to retaliate with an alternative bundle, producing the same degree of political targeting, while likely producing less domestic economic damage.

Our results contribute to the literature on the political economy of protectionist trade policies. Economists have long studied the political economy underlying trade conflicts. Given the large literature on the welfare-enhancing effects of trade (e.g. [Ricardo, 1891](#); [Hecksher and Ohlin, 1933](#); [Frankel and Romer, 1999](#); [Baldwin, 2004](#), to name just a few), it is widely accepted that erecting tariff barriers, while able to help certain individual industries, are not only harmful to trading partners but also constitute an act of self-harm ([Bown, 2004](#); [Breuss, 2004](#)). To offer an explanation why politicians nonetheless often favour tariffs, the imposition of domestic tariffs has been attributed to either the influence of interest groups ([Grossman](#)

and Helpman, 1994), peoples inequity aversion (Lü et al., 2012), the importance of tariffs as a source of revenue (Hansen, 1990), the structure of consumer tastes (Baker, 2005) along with the relative factor endowments (Scheve and Slaughter, 2001). Existing research further suggests that democracies are more likely to lower tariff barriers, but are more likely to protect their agricultural sectors and make use of non-tariff barriers (NTB) (Kono, 2006; Barari et al., 2019, e.g.). Cameron and Schuyler (2007) investigates the determinant of protectionism in the agricultural sector. In closely related work Gawande and Hansen (1999) investigate the deterrence effect of NTB and how retaliatory NTB can be used to reduce foreign trade barriers. Our findings shed light on how other countries react to protectionism and the US's aggressive trade policy. To the best of our knowledge, we are the first to empirically document the trade-offs underlying retaliation design.

Recent work by Fajgelbaum et al. (2020) and Amiti et al. (2019) investigate the economic impact of Trump's trade war on US consumers. This paper is different in at least two dimensions. First, rather than focusing on the economic impact of tariffs, we aim to shed light on how trade partners respond to the US's unilateral imposition of protectionist measures. Second, using a novel simulation approach, we can trace out the underlying trade-offs that countries or trading blocs navigate when designing a retaliation response. In this way, our paper provides new insights into the political economy of retaliatory tariffs.

Secondly, our paper also speaks to the political effects of trade integration. Building on the seminal work by Autor et al. (2013), a significant literature is studying the political implications of these economic shocks. Autor et al. (2016); Che et al. (2017); Colantone and Stanig (2018a,b); Dippel et al. (2015) each doc-

ument, in the context of the US, the UK, Germany, and Western Europe more broadly, that areas most exposed to import competition saw a rise in populism or political polarization. [Feigenbaum and Hall \(2015\)](#) further show an impact on US trade policy: politicians from districts most exposed to the “China-shock” shifted to vote in a more protectionist direction on trade-related bills using roll call data. [Autor et al. \(2016\)](#) and [Che et al. \(2017\)](#) suggest that the election of Donald Trump, on a nativist America First platform, was significantly shaped by votes coming from areas that suffered most strongly from import competition with low-income countries. [Scheve and Slaughter \(2004\)](#) highlights that even indirect trade-exposure may This paper study the flip-side of the story and looks at whether retaliatory tariffs are aimed at counties or parts of the US with tradable-goods producing sectors that have survived the “China shock”.

In other related research, economists have analyzed the economic and political targeting of sanctions (e.g. [Elliott and Hufbauer, 1999](#); [Eaton and Engers, 1992](#); [Ahn and Ludema, 2017](#)). [Kavaklı et al. \(2020\)](#) find that comparative advantage in exports and domestic production capabilities determine a countries’ ability to minimize costs while maximizing its power to hurt in the context of economic sanctions. While tariffs have mainly been studied as an economic tool, sanctions have been understood as a political tool to induce compliance. In this literature, [Marinov \(2005\)](#) and [Allen \(2008\)](#) provide evidence that sanctions increase the probability of leadership change. In other work, [Draca et al. \(2018\)](#) show that US sanctions against Iran are effective in targeting politically connected firms and actors. Despite the fact that compared to sanction, retaliatory tariffs are far more limited in scope and intensity, our findings suggest that also retaliatory tariffs are used as

a political tool.

The rest of the papers proceeds as follows. Section 2 describes the political context and the data used in the empirical analysis. Section 3 shows the extent of political targeting of tariffs. Afterwards, Section 4 introduces our simulation approach and provides evidence for the trade-off between political targeting and domestic harm. Section 5 concludes.

2 Context and Data

The international trading system after the Second World War was first institutionalized through the General Agreement on Tariffs and Trade (GATT) in 1948. It was a direct result of the failings of the international trade system during the Great Depression. In 1930, the Smoot-Hawley Act increased tariffs on more than 20,000 products imported by the US. This set off a tit-for-tat retaliation. [Irwin \(1998\)](#) estimates that nearly a quarter of the observed 40% decline in imports can be attributed to the rise in the US tariff and thereby contributed to the lengthening of the Great Depression.

Through multiple GATT rounds from 1948 onwards, average tariff rates were reduced significantly. One of the most important features of the international trading system which is now regulated by the WTO – the successor organisation to the GATT established in 1995 – is a formal Dispute Resolution System. In principle, governments are still able to restrict trade to foster non-economic social policy objectives, to ensure “fair competition”, or to support preferential treatment of developing countries, regional free trade areas and customs unions. But measures of this kind are subject to scrutiny, should adhere to the broad principles of the WTO

and can be contested by WTO member countries by invoking the WTO's Dispute Resolution mechanism. [Rosendorff \(2005\)](#) and [Sattler et al. \(2014\)](#) provide evidence that the WTO's Dispute Resolution mechanism helps to enforce stable trade relationships. The Dispute Resolution mechanism also regulates the imposition of retaliation measures.

2.1 Retaliatory Tariffs as a Political Tool

The most recent precedent in which the international trading system came close to a similar escalation were steel tariffs imposed by President George W. Bush, which took effect March 20, 2003. The US justified the tariffs as an anti-dumping response and in contrast to the current spate, NAFTA partners were exempted from the tariffs. The EU and other trading blocs immediately filed a dispute with the WTO. On November 11, 2003 this resulted in a verdict against the US and tariffs were abolished on December 4, 2003. The WTO ruling implied that the anti-dumping justification for the tariffs was void, as the US had in fact been importing less steel compared to previous years in 2001 and 2002. The ruling authorized more than \$2 billion in sanctions against the US. President George W. Bush initially wanted to preserve the tariffs. Though, following threats of retaliation by the European Union, the US backed down and withdrew the tariffs.

While this does not prove that the threat of retaliation was the reason why tariffs were abandoned, it does suggest that it may have played a role. The European Commission stands out in terms of transparency regarding the objectives it aims to achieve in the context of trade disputes (see [Baccini, 2010](#); [Stasavage, 2004](#) on the role of transparency). Specifically, EU Regulation 654, published in 2014, outlines three objectives for commercial policy measures in the context of a trade dispute:

“Commercial policy measures [...] shall be determined on the basis of the following criteria, in light of available information and of the Union’s general interest:

- (a) effectiveness of the measures in inducing compliance of third countries with international trade rules;
- (b) potential of the measures to provide relief to economic operators within the Union affected by third country measures;
- (c) availability of alternative sources of supply for the goods or services concerned, in order to avoid or minimise any negative impact on downstream industries, contracting authorities or entities, or final consumers within the Union;

In other words, trade policy should aim to change the trade policy of the opposing country, while minimizing harm to the own economy.

To design the retaliation response, the European Commission is known to use an algorithm to select products against which retaliatory tariffs are targeted. This algorithm is naturally a safely guarded secret.¹

The Chinese government does not publish its policy objectives in the trade dispute, but there is evidence that they also try to target their tariffs against the electoral base of Donald Trump and the Republican party. For example, the Chinese as well as the EU’s retaliation targeted bourbon whiskey produced in Kentucky, the home state of Senate majority leader Mitch McConnell. Also, the Wisconsin congressional district of then Speaker of the House Paul Ryan was targeted with retaliatory tariffs on cranberries and cranberry products. Moreover, China and

¹One of the authors of this paper had a conversation with an anonymous senior EU commission source, who referred to the algorithm as the EU’s “weapon of war” in the context of the trade dispute, indicating why it is a closely guarded secret.

Mexico targeted pork and soybeans, which disproportionately affected Iowa, the home state of influential Republican Senate Agriculture Committee member Senator Charles E. Grassley. These examples suggest that the design of retaliatory tariffs shares some similarities with political sanctions. The growing literature on sanctions understands sanctions as a political tool to induce compliance (see for example [Elliott and Hufbauer, 1999](#); [Eaton and Engers, 1992](#); [Ahn and Ludema, 2017](#)). In contrast, the political dimensions of tariffs so far have been widely ignored. In our analysis, we investigate to what degree the retaliating countries indeed systematically politically targeted their retaliation. For our analysis, we construct a measure of exposure to retaliatory tariffs for each US county, which we discuss next.

2.2 Descriptives of the retaliation measures

The retaliation measures against the US tariffs take the form of a list of products with descriptions and (typically) the Harmonized System (HS) code along with an (additional) tariff rate to be imposed on imports of these goods stemming from the US. These lists are prepared through a consultative process in the case of the EU and Canada. They are lodged and registered with the WTO and, there is typically a delay prior to the tariffs being implemented. For our analysis, we have obtained retaliatory tariff lists from the EU, China, Mexico, and Canada. We do not analyze the retaliation of other countries such as India and Turkey, as the overall trade volume and therefore the retaliation is far smaller.²

²The official retaliation lists are available here: EU, <http://trade.ec.europa.eu/doclib/press/index.cfm?id=1842>, China, <http://english.mofcom.gov.cn/article/newsrelease/significantnews/201806/20180602757681.shtml>, Mexico, http://www.dof.gob.mx/nota_detalle.php?codigo=5525036&fecha=05/06/2018 and Canada <https://www.fin.gc.ca/activty/consult/cacsap-cmpcaa-eng.asp>, accessed 18.08.2018.

Appendix Figure A1 visualizes the distribution of the retaliation measures across coarse economic sectors. The figure suggests similarly, that manufacturing sector outputs, as well as agricultural commodities, were significant features in the retaliation lists. We next describe how we use the retaliation list to construct a county's exposure to tariffs.

2.3 Measuring exposure to retaliation

We use two data sources to construct a county-level measure of exposure to retaliation measures. First, we use data from the Brookings (2017) Export Monitor. This data contain a measure of county-level exports across a set of 131 NAICS industries.³ We denote $X_{c,i}$ the export of industry i for each county c . The data also provides an estimate of the total exports at the county level and the number of export-dependent jobs.

Secondly, we use the individual retaliation lists \mathcal{L}_r for $r \in \{EU, MX, CA, CN\}$. These are matched at the 8-digit HS level to the US trade data using export volume.⁴ We validate our mapping by comparing the resulting value of trade flows affected by tariffs with the official WTO submissions. For this exercise, we make use of HS-level U.S. import and export data from the U.S. Census Bureau.⁵ In the case of the EU, the retaliation measures officially target trade worth USD 7.2 billion. Matching the EU list to the US trade data for 2017, we find that US ex-

³The data incorporates a host of data, including US goods trade data, service-sector export data from the Bureau of Economic Analysis (BEA), Internal Revenue Service (IRS) data for royalties, Moody's Analytics production estimates at the county level, and foreign students' expenditures from NAFSA. More details on Brookings (2017) can be found <https://www.brookings.edu/research/export-nation-2017/>.

⁴While technically the codes of products are provided at the 10 digit level, the matching results are best at the 8-digit HS level due to slight discrepancies in the coding standard across countries. This introduces only a small amount of inconsequential noise.

⁵These data can be found here <https://usatrade.census.gov/>.

ports worth USD 7.6 billion are affected by retaliation, suggesting that the overall magnitude is similar.

To link the targeted exports to the different six-digit NAICS sectors that produce the goods (HS10 codes), we use the concordances between HS codes and NAICS/SIC codes from [Schott \(2008\)](#). These concordances provide up to 10 digit commodity codes, which map into the Harmonized System codes used, together with SIC and NAICS codes. This allows us to merge the tariffs lists with the employment data. In case multiple sectors are linked to an HS10 code, we retain the NAICS sector listed first in the concordance. As an illustration, consider the example of the EU's rebalancing measures, which includes the item "10059000 Maize (excluding seeds for growing)". This HS code is mapped to the NAICS industry 111150, which stands for "Corn Farming". This procedure results in a list of *tariff exposed industries*.

Next, we collapse the total volume of affected trade to the four digit industry level. This gives us a measure of total exports $T_{i,r}$, from four digit industry i , that was affected by retaliatory tariffs of country r . We break this measure down to the county level based on the share that the exports from county c makes up of all exports for goods attributed to industry i . Let $X_{c,i}$ denote the exports from county c in industry i . The share is then given as $\frac{X_{c,i}}{\mathbf{X}_i}$, where $\mathbf{X}_i = \sum_c X_{c,i}$. The product $\frac{X_{c,i}}{\mathbf{X}_i} \times T_{i,r}$ provides the volume of exports stemming from county c and industry i that is subject to retaliation. We aggregate this measure up across all industries i to arrive at the total value of exports from county c subject to retaliation from retaliation list r . In the last step, this measure is normalized by the total value of

exports from county c as $\mathbf{X}_c = \sum_i X_{c,i}$.⁶

The final exposure measures $\tau_{c,r}$ for county c and list of retaliatory tariffs r is given as:

$$\tau_{c,r} = \frac{\sum_i \frac{X_{c,i}}{\mathbf{X}_c} \times T_{i,r}}{\mathbf{X}_c}$$

These measures approximates the exposure of counties to retaliation measures of each retaliating country r . The measure is bounded between 0 and 1. If industries in a county are unaffected by tariffs the measure is 0. If the entire production of a good subject to retaliation were to take place in a single county and if that county were to export only this good, the exposure measure would be 1.

Our approach is similar to the [Autor et al. \(2013\)](#)-type labor market shocks. The main difference is that rather than constructing this measure based on sector level employment figures, our measure is based on sector level output figures. This should come closer to capturing the economic impact more broadly. As a robustness check, we consider an alternative exposure measure based following [Autor et al. \(2013\)](#) and [Kovak \(2013\)](#), which uses the County Business Patterns (CBP) employment data to construct a county-level retaliation exposure based on sector-level employment shares. In Appendix Table [A1](#) we show that results are similar when using this alternative measure.⁷

Since the added tariff rate was set at 25% for 85% of the products, our retaliation exposure measure ignores the actual added tariff rate. This also implies that

⁶In Appendix Table [A2](#) we show that the results also hold when we normalize our measure by population instead.

⁷This is not surprising, as under certain assumption on the production functions the measures would be identical.

the variation in our county-level exposure measure $\tau_{c,r}$ is driven by the *choice of products* and not the choice of tariff rates. While this is only a small deviation from the actual data, it greatly simplifies the simulation of counterfactual retaliation baskets in Section 4. In Appendix Figure A2 we compare our exposure measure with the exposure measure that would result if we incorporate the actual added tariff rate. The two measures are statistically virtually identical.

2.4 Main political outcome measures

In the following, we describe the aggregate and individual-level data sources used to measure the extent of political targeting.

Aggregate election results We leverage election results data collated by Dave Leip. This data provides us with county-level election outcomes, specifically for the recent 2008, 2012, 2016 presidential elections, the House and Senate elections as well as for the 2018 midterm elections. While the natural resolution for House election is the Congressional District level, unfortunately, our retaliatory tariff exposure measure is not available at the congressional district level.

Gallup daily tracker We make use of the Gallup Daily Tracker data from 2012 covering the period up to mid 2018. The data is a repeated cross-section containing the county of residence of individual respondents. Our primary focus is on three types of measures: the individual-level party affiliation, the presidential approval ratings and the expressed support for the candidates in the 2016 election. The data are particularly useful as the underlying samples are large enough to study how the correlation between an individual’s republican party identity and the county-level exposure to retaliation evolved over time. As the underlying micro-data do

not provide information on actual voting or voting intention, we use an additional individual-level data set with a quasi-panel structure.

Cooperative Congressional Election Study The Cooperative Congressional Election Study (CCES) is a large survey that consists of two waves in election years comprising a pre- and post-election wave (see [Ansolabehere and Rivers, 2013](#) for more detail). The survey around the 2016 presidential election also asked how individuals voted in the preceding 2012 presidential election. This allows us to study the data in first-difference to shed some light on whether retaliation appears targeted towards areas that saw swings in political support. Further, the CCES makes it possible to narrow down to the set of respondents who have voted based on the national voter file of over 180 million records (see [Enamorado and Imai, 2018](#) for a description of the method).

While the primary focus of this paper is to show that retaliation is carefully politically calibrated, the trade-war and retaliation also do have pure economic effects. In related work, [Fajgelbaum et al. \(2020\)](#) and [Amiti et al. \(2019\)](#) study the implication of the trade war on consumer welfare and prices. In [Appendix 2](#) we provide some auxiliary evidence that complements their work suggesting that retaliation was indeed effective in reducing US exports and lead to a drop in export prices, suggesting that exposure to retaliation produced indeed an economic shock.

3 Was the retaliation politically targeted?

3.1 Descriptive evidence

We first provide descriptive evidence that counties with stronger support for the Republican party were more heavily targeted by tariffs. Figure 1 plots the retaliation exposure from the different trading partners for each US county. The figure highlights that the retaliatory tariffs from China, the EU, Canada, and Mexico affected different counties. Further, Panel A and Panel B of Figure 2 suggests a clear pattern whereby counties with a stronger leaning towards the Republican party were more heavily targeted by tariffs. The same holds true for counties that saw a bigger swing to Trump in the 2016 presidential election. We explore this further in a regression framework.

3.2 County-level data

Empirical specification To understand to what extent retaliatory measures disproportionately targeted Republican counties within the US, we estimate the following regression equation:

$$y_{c,s} = \alpha_s + \beta_r \times \tau_{c,r} + \epsilon_c \quad (1)$$

In this specification, $y_{c,s}$ measures the vote share of the Republican party in county c in state s in 2016. As an alternative outcome we use $\Delta y_{c,s}$, the change in the Republican party vote share between the 2012 Presidential election and the 2016 Presidential election at the county level. $\tau_{c,r}$ is the county level exposure measure for retaliatory tariffs list r (for more details see Section 2.3). All regressions

includes state fixed effects, hence we exploit within-state variation in retaliation exposure. Standard errors are clustered at the county level.⁸

Results The results from the estimation of model 1 are presented in Table 1. The results suggest that counties which are more exposed to retaliatory tariff had higher levels of support for Trump in the 2016 presidential election. Further, as indicated in Panel B, counties exposed to retaliation also saw larger swings in support from the 2012 Presidential election to the 2016 Presidential election. The point estimate in column (2) suggests that the counties most exposed to EU retaliation saw an average swing in the Republican candidates' vote share of 22 percentage points vis-a-vis counties not exposed to EU retaliation.

As the retaliation exposure measures $\tau_{c,r}$ are bounded between zero and one the coefficients are directly comparable. We find, that the degree of political targeting is strongest for the EU and Mexico's retaliation. We will revisit this result in our simulation study in Section 4. Before turning to the individual-level data, we next conduct further robustness checks for our baseline findings.

Robustness We first explore whether the targeting was stronger for the presidential election than for the House and Senate election held on the same day (Tuesday, November 8, 2016). The results of this exercise can be found in Appendix Table A3. Panel A explores Republican party vote shares. Throughout, there is a strong positive correlation – yet, we find no evidence for differences in targeting across election types. In Panel B we compare the changes in Republican candidate vote share vis-a-vis the elections held in 2012 (for Presidential and House elections). For the Senate election, we compare the change with the most recent prior Senate

⁸We show that our main results are robust to alternative levels of clustering as well as Conley standard errors in Online Appendix Table A4.

election for Senators (as only 1/3 of Senators are up for election each time). In this specification, it appears that the regression coefficient for retaliation exposure is markedly larger for the Presidential election but not for Republican candidates across other election types. This holds true despite the fact that voters could vote *on the same day in 2016*. This provides some additional evidence that retaliation may have been targeted to hit areas that swung behind Trump in 2016. A potential rationale behind such a strategy could be that these voters may conceivably swing back (see [Alesina and Rosenthal, 1995, 2006](#) or [Scheve and Tomz, 1999](#) for work studying the dynamics of US presidential and midterm elections).

In Appendix Table [A5](#) we highlight that the correlation between retaliation exposure and (shifts in) support of Republican presidential candidates is distinctly stronger for the 2016 election. We investigate this observation further in the individual level analysis. Our findings are similar when we use an alternative exposure measure based on the sector-level employment shares inspired by [Autor et al. \(2013\)](#) (see Appendix Table [A1](#)).

Lastly, in Appendix Table [A6](#) we show that our results are robust to the inclusion of additional control variables.⁹ First, we control for a county-level measure of the China shock used in [Autor et al. \(2013\)](#). This control is motivated by the work of [Autor et al. \(2016\)](#) who find that Trump performed better in counties that were more exposed to Chinese import competition.¹⁰ In line with this result, we find that the estimated coefficient on the China shock is positive and significant. Yet, our retaliation exposure coefficient hardly changes. This is not surprising for

⁹Note that we focus on the combined retaliation exposure measure. The patterns are very similar when analyzing country-by-country.

¹⁰Similar effects have been documented in the context of the UK and Western Europe more broadly ([Colantone and Stanig, 2018a,b](#)); [Feigenbaum and Hall \(2015\)](#) shows that politicians from districts most exposed to the “China-shock” became more protectionist in direction.

two reasons. Naturally, a county's exposure to retaliation depends on the structure of trade between the US and the trading partner. Retaliation exposure is driven by US exports, while the China shock is based on US imports. In addition, trade-dispute induced retaliation can only produce economic shocks in regions and parts of the US in which the tradable-goods producing sectors have survived the "China shock".¹¹ We also control for the level (and changes) in turnout in the 2016 presidential election. [Guiso et al. \(2018\)](#) suggest that the ability for populist candidates to affect turnout may be a key feature to understanding their success. Indeed, in Appendix Table [A7](#) we document that places more exposed to retaliation saw, on average, lower levels of turnout. Yet, our observation suggesting that retaliation was politically targeted remains intact.¹²

3.3 Cross-sectional individual-level data

We use repeated individual-level cross-sectional data from the Gallup Daily Tracker. This allows us to study the extent of support for Donald Trump using individual-level micro data allowing us to control for a set of potential confounders. Further, we can exploit variation over time and draw comparison to other Republican candidates.

Empirical specification To leverage individual level data we modify our above regression specification in the following way:

$$y_{i,c,t} = \alpha_s + \nu'X_i + \beta_r \times \tau_{c,r} + \epsilon_c \quad (2)$$

¹¹This fact can also be seen in Appendix Figure [A3](#), which shows that the relationship between tariff exposure and the China shock is negative.

¹²As an alternative way to address the concerns of committed county characteristics, we perform a matching exercise. The results of this exercise are reported in Appendix Tables [A8](#) and [A9](#).

In this regression $y_{i,c,t}$ measures whether an individual i in county c in year t has a favorable view of Donald Trump as candidate. In our analysis, we focus on the period from June 2015 to March 2016 prior to the election and prior to Donald Trump becoming the presumptive nominee. This allows us to compare the degree of targeting for other Republican candidates who were (still) in the race at the same time. The specification controls for state fixed effects α_s as well as a set of individual controls X_i . In particular, we control for the respondents race across five categories, income across 12 categories, gender and the year of the survey. In specifications where the dependent variable is not party-affiliation, we also control for an indicator whether a respondent describes themselves as Republican or leaning Republican.

Since the Republican party affiliation is observed consistently from 2012 onwards, we can further estimate a flexible difference-in-difference specification:

$$y_{i,c,t} = \alpha_c + \gamma_t + \nu' X_i + \sum_{t=2012}^{2018} \beta_{r,t} \times \tau_{c,r} + \epsilon_c \quad (3)$$

Since the regression contains county fixed effects α_c and time fixed effects γ_t , the coefficient $\beta_{r,t}$ captures the differential *changes* in individuals' leaning towards the Republican party and our county-level measure of retaliation exposure. In other words, $\beta_{r,t}$ picks up whether areas more exposed to retaliatory tariffs exhibited shifts in the support for the Republican party relative to previous years. If retaliation was indeed targeted to counties with a Republican voter base that identifies with Donald Trump, we would expect the correlation between individual respondents self-reported affinity towards the Republican party and the county-level retaliation exposure measure to increase with Trump's presidential run. Further,

this analysis will also show whether there were changes in Republican support before Trump’s campaign started. In this way, we can disentangle general shifts in political preferences or party affiliation from support for Trump as a candidate.

Results In Table 2, we show that retaliation is again highly correlated with measures of approval for Donald Trump both as candidate (Panel A) and as President (Panel B). Retaliation is also much more likely to affect parts of the US where respondents have an affinity towards the Republican party (Panel C). Consistent with the previous observation, the results suggest that the retaliation by the EU and by Mexico appears more distinctly targeted.

For the EU retaliation exposure individuals living in counties with the highest retaliation exposure would be characterized by a 31.5 percentage point higher propensity to express a favorable view of Trump as a candidate. For the Chinese retaliation, a county subject to an equivalent retaliation exposure is characterized by an 11.6 percentage point higher individual self-reported propensity to have a favorable view of Trump.

A potential concern with these findings could be that the retaliation patterns simply capture geographic differences of republican versus democratic support. To highlight that retaliatory tariffs indeed appear to target areas with strong support for Donald Trump, we analyze the period in which the Republican nomination was still open and included Donald Trump as a candidate (July 2015 onwards until March 2016).¹³ We further focus on the subset of respondents who self-identify as

¹³Donald Trump announced his candidacy formally on June 16, 2015 and became the presumptive nominee on May 4, 2016. We focus on the period between his announcement until March 2016 to have a consistent sample for comparisons across the four main Republican candidates Marco Rubio, Ted Cruz, John Kasich and Donald Trump who survived the race up until March. From March 16 onwards Marco Rubio dropped out of the race and it appeared increasingly unlikely that Trump could be denied the nomination.

Republican ($\approx 23.4\%$ of the sample). With this analysis we aim to capture whether retaliation exposure was distinctively targeted against areas who supported Trump instead of another Republican presidential candidate.

The results are presented in Table 3. Throughout Panels A - D the dependent variable is a dummy indicating whether a respondent expresses a favorable opinion for the Republican presidential candidate indicated in the panel label. The results indicate a clear pattern. The EU and the Chinese retaliation particularly target part of the US in which Trump was more popular among self-identifying Republicans. In contrast no such relationship exists when we consider the support for any of the other presidential candidates. For the Mexican and the Canadian retaliation the correlation is also positive, but statistical insignificant. This finding suggests that retaliation was carefully chosen to target areas with Republican supporters with an affinity for Donald Trump. The specific targeting of Trump's voter base, exhibits parallels to the targeting of politically connected firms by economic sanctions in Iran (Draca et al., 2018), both of which are likely to increase the pressure on the respective political leader.

Lastly, in Figure 3 we present the estimated difference-in-difference coefficients from specification 3. The figure suggests that the correlation between a county's exposure to retaliation and individuals' leaning towards the Republican party becomes distinctly stronger from 2016 onwards. This suggest that retaliation was targeted against areas which increased their support for the Republican party relative towards the 2015 baseline level. In other words, areas that during Trump's presidential run were swayed to support Republicans were more strongly targeted than areas that always exhibited a strong support of the Republican party. It is also

worth noting that trends prior to 2015 are flat. This suggests that our retaliation measure is not confounding other latent trends in the geography of Republican party affiliation that pre-date Donald Trump’s candidacy.¹⁴ If we were simply picking up the trade-induced manufacturing sector decline (Autor et al., 2016), for example, this trends should be visible before the 2016 presidential election

We next explore a short individual-level panel highlighting that retaliation, especially from the EU and China, was targeted to the US that saw sizable swings from Obama in 2012 to supporting Trump in 2016.

3.4 Individual-level panel data

As an additional piece of evidence, we leverage the 2016 CCES study which asked the respondents if and for whom individuals voted in the 2012 and 2016 Presidential elections. The advantage of the CCES in comparison to the Gallup data is that it directly measures voting behavior instead of approval or party affiliation. In this way, the CCES data allow us to study whether individuals switched their party support vis-a-vis the 2012 election. We estimate regression specification 2. The set of individual-level controls X_i includes race, gender, age, income and political party affiliation. As we estimate the regression in first-differences, we implicitly accounting for time-invariant individual-level characteristics (similar to individual fixed effects). In particular, we study the direction of the switch – i.e. whether retaliation was concentrated in counties with voters that swung from supporting Barack Obama to supporting Donald Trump. The results from this analysis are presented in Appendix Table A10.

¹⁴For example, the growth of partisan media (DellaVigna and Kaplan, 2007; Levendusky, 2013), gerrymandering (McCarty et al., 2009), intra-party political movements (Madestam et al., 2013; Williamson et al., 2011), geographic polarization (Martin and Webster, 2018)).

The patterns are very similar and consistent with the previous results on the county-level and from the Gallup tracker. In Panel A, we focus on self-reported voting for Donald Trump in 2016, while controlling for Republican party affiliation. magnitudes of the point estimates suggest that in counties most exposed to EU retaliation, voters' propensity to support Donald Trump in 2016 was 62 percentage points higher.

We also explore the targeting properties studying voter-moves between candidates in 2012 and 2016 in Panel B and C. The point estimates suggest that the retaliation appears to target counties with more swing voters. Specifically, in Panel C, we focus on voters who swung from supporting Barack Obama in 2012 to supporting Donald Trump in 2016, with results suggesting that retaliation was mainly targeted to hit counties that saw voters switch from Obama to Trump.

The estimates are statistically significant for the EU and the Chinese retaliation exposure measures. The point estimates suggest that in counties most targeted by EU retaliation, the likelihood of an individual voter to be a swing voters that switched from supporting Obama to Trump is 7.6 percentage points higher. For counties exposed to Chinese retaliation at the same level, the likelihood is 3.8 percentage points higher.¹⁵

Taken together, the results suggest that retaliation appears to have been chosen to target counties in which Trump had a particular appeal and voters increased their support for the Republican party. The patterns documented across three different data sources are remarkably consistent. Additionally, the fact that the Trump administration provided billions of dollars in farm aid packages (see for

¹⁵In Appendix Table A11 we confirm the results for the subset of voters for which their voting status has been validated based on official voter lists. The patterns remain broadly the same, even though we do lose some statistical precision.

example [NYT, 2018](#)), suggest that the effect of retaliatory tariffs was felt in the targeted areas. In [Appendix 2](#) we provide auxiliary evidence for the economic consequences of the tariffs. In line with the findings of [Levitt and Snyder \(1995\)](#); [Berry et al. \(2010\)](#) on pork barrel spending, the farm aids can be interpreted as an attempt to mitigate the political fallout from the trade war.

A remaining concern is that the underlying patterns could be spurious in a fashion that can not be accounted for with individual level or other county-level control variables. Specifically, one might worry that the specific mix of products that countries purchase from the US may mechanically constrain the structure of *any* retaliation response. To address this concern we exploit the fact that for the initial wave of tariffs – which we study in this paper – the constraints on the retaliation response are quite well defined. This allows us to construct counterfactual baskets countries could have chosen and evaluate the degree of political targeting against these counterfactuals. These counterfactual baskets additionally allow us to investigate other constraints on the retaliation response.

4 Counterfactual retaliation baskets

Is the observed targeting of Republican counties a mere artefact of the US export mix with specific trading partners and do trading-partners face trade-offs due to domestic constraints? In this section, we attempt to answer these questions by proposing a simulation approach exploiting retaliation design constraints to construct feasible counterfactual retaliation baskets.

4.1 Retaliation design constraints

In our simulations, we leverage the fact that trading rules impose constraints on the design of retaliation (or more formally, rebalancing measures). The key constraint is that the applied retaliatory tariffs should be commensurate with the US tariffs. For example, the tariffs imposed by the US on steel and aluminium affected around USD 7.2 billion of EU exports to the US with an expected added overall tariff revenue volume of USD 1.6 billion.¹⁶ To comply with WTO rules, the EU's expected tariff revenues from the retaliation should not exceed this amount.

Our aim therefore is to identify a vector of products i among all traded HS goods categories for which there is non-zero imports, $M_{i,r} > 0$, into retaliating country r along with a vector non-zero tariff rates $t_{i,r} > 0$ to be applied such that the combined expected tariff revenues $\sum_{i \in \mathcal{S}_r} t_{i,r} M_{i,r}$ is less than the expected tariff revenues that the US levies on imports from country r , T_r . As previously discussed, the choice of the tariff rates is secondary for the retaliation wave we study: for 85% of product classes included in the actual retaliation the added tariff rate was fixed at 25%. For the counterfactual construction we, therefore, ignore the choice of the added tariff rate $t_{i,r}$ implicitly assuming a fixed rate t .¹⁷ With a fixed tariff rate the above problem becomes a *subset sum* problem.

Nevertheless, even this subset sum problem is computationally difficult to solve. A subset-sum problem is NP-complete, meaning that the most efficient algorithm to find a solution have a running-time of order $O(2^{\frac{N}{2}})$, where N is the number of elements in the set. In our case, the exponential growth of the running

¹⁶See https://europa.eu/rapid/press-release_IP-18-4220_en.htm, accessed 18.07.2018.

¹⁷In Appendix Figure A2 we highlighted that the implied county-level retaliation exposure measure accounting for the actual tariff rate vis-a-vis the measure that ignores the rate are statistically virtually identical.

time combined with the large number of potential HS product codes to choose from makes it computationally infeasible to derive the complete set of possible retaliatory baskets. To illustrate: at the 8-digit HS code level, there are around 4,000 goods for which US imports to the EU exceeded USD 1 million in 2017; further, there are around 400 goods for which imports exceeded USD 100 million in 2017 (see Figure A4). This potentially leaves an uncountably large set of combinations of products for which the combined affected imports from the US is approximately equal to the US tariffs. To overcome this challenge, we use a probabilistic simulation approach to identify a set of alternative baskets

4.2 Simulation approach

In particular we use the following sampling procedure for each country's retaliation list L :

```

while less than 1000 alternative retaliation baskets  $\mathcal{L}_{r,i}$  have been found: do
  1. Randomly draw an integer  $N_i$  indicating length of retaliation list in terms of
    HS10 codes – allow for a 20% deviation around list length of actual
    retaliation  $N_{r*}$ 
  2. Draw a sample list  $\mathcal{L}_{i,r}$  of HS10 codes of length  $N_i$  on which there is some
    exports from the US in 2017
  3. Compute the volume of exports from US to country  $r$  that would be affected
    by retaliation if the sample list  $\mathcal{L}_{i,r}$  were chosen  $\sum_{i \in \mathcal{L}_{i,r}} E_{i,US,r}$ 
  4. if  $0.9 < \frac{\sum_{i \in \mathcal{L}_{i,r}} E_{i,US,r}}{\sum_{i \in \mathcal{L}_r^*} E_{i,US,r}} < 1.1$  then
    | Accept the candidate list  $\mathcal{L}_{i,r}$ ;
    end
end

```

As indicated in the pseudo-code we construct counterfactual retaliation list by

first choosing a similar number of products to target (allowing for 20% deviation). We then sample a set of products to target and calculate the effected export volume. Lastly, we accept any list which affects a similar amount of exports as the actual list (allowing for a 10% deviation). The result of our sampling procedure is a set of retaliation lists that are similar to the original list in many dimensions, but target a different set of US exports. While the simulation approach traces out some aspects of the “retaliation possibilities frontier”, it ignores two potential strategic elements. First, retaliation lists may be designed in a way to preserve an option value to hit back in case of a further escalation. Second, retaliating countries may coordinate their retaliation responses to maximise the effectiveness. It is also important to note, that the counterfactual retaliation bundles are not orthogonal to the actual retaliation basket (see Appendix Figure A5). The observed positive correlation mechanically results because the simulated baskets overlap with the actual retaliation basket.

4.3 Evaluating the degree of political targeting

The simulation approach is particularly useful as it allows us to *quantify* the degree of political targeting relative to the counterfactual baskets. More specifically, we evaluate whether retaliation appears at the upper- or lower end of the potential retaliation distribution. We also investigate the underling trade-offs that countries face in their retaliation design. For this analysis, we estimate the regression models studied in the previous Tables 1, 2 and Table A10 for counterfactual retaliation list and the implied counterfactual county-level retaliation exposure measures.¹⁸ The

¹⁸Note that there is a non-negligible cross-correlation across retaliation bundles. Appendix Figure A5 highlights that the implied measures and the actually chosen retaliation response have a positive correlation almost across each of the 1000 counterfactual bundles. This is a mere direct

result of this exercise is a vector of estimates $\hat{\beta}_r = (\hat{\beta}_r^1, \dots, \hat{\beta}_r^{1000})$ measuring the correlations between the simulated counterfactual tariff exposure measures and the outcome of interest (e.g. Republican vote share). We this vector of estimates relative to the estimate $\hat{\beta}_r^*$ for the actual retaliation list \mathcal{L}_r .

Table 4 presents the share of the counterfactual estimates $\hat{\beta}_r$ that would imply a higher level of political targeting. In column (1) and (2) we focus on the outcomes studied in Table 1. Column (1) suggests that for China, there exist hardly any feasible and comparable retaliation responses that would produce a stronger (conditional) correlation with the 2016 Republican vote share. For the EU, around 29% of bundles would have a higher degree of political targeting. For Canada and Mexico, these numbers are 73.4% and 51.2%. This suggests that retaliation of these countries could have been designed in a fashion that achieves a higher degree of targeting on this particular moment. In column (2), we study the changes in the Republican vote share from 2012 to 2016. The EU and China's retaliation response again appear more targeted than most counterfactual baskets. For Canada and Mexico, the measures are in the middle of the counterfactual distribution. This again suggests that retaliation could have been chosen to produce a higher degree of political targeting. In columns (3) - (7) we study the other outcome measures explored in Tables 2 and Appendix Table A10. They observed patterns are broadly similar.

The finding that Canadian and Mexican retaliation, while being quite robustly associated with support for Donald Trump, does not appear to be at the upper end of the achievable targeting distribution, suggests that other considerations

result of the retaliation response that meet the criteria to be quite similar will produce some overlap, implying a mechanical cross-correlation.

may have played just as important a role. We next aim to investigate which other objectives countries might include in their considerations.

4.4 Retaliation trade-offs

The previous section suggests that retaliation appears to specifically target parts of the US that swung to support Donald Trump. Yet, relative to a set of counterfactual retaliation responses, especially for Canada and Mexico, we observed that the implemented choice seems suboptimal. What may explain this observation? As our discussion of the EU's retaliation design objectives suggested, countries designing the retaliation have multiple objectives. In the EU regulation constraining retaliation design, the mitigation of harm to consumers and firms features prominently along with the political effectiveness. In this section, we construct a set of relevant measures that might constrain the retaliation choice. In particular, we investigate the role of the revealed comparative advantage, the import demand elasticities and the dominance of US exports.

Revealed comparative advantage The first measure is an index of the revealed comparative advantage (henceforth, RCA) as introduced by [Balassa \(1965\)](#). The intuition for this index, which is constructed based on export data, is that countries appear to have a revealed comparative advantage for a good h if a higher share of the countries export is accounted for by this good relative to the export share of this good across all trading countries. Formally, an RCA value above 1 for a specific good h indicates that a country has a revealed comparative advantage (see [Kavakli et al., 2020](#) for a recent example using RCA measures in the context of economic sanctions). When designing their retaliation response countries reasonably might want to avoid goods for which the US has a Revealed Comparative Advantage.

We denote the implied average RCA for each retaliation list as $RCA_{i,r}$, which we weight by the implied volume of trade.¹⁹ As the construction of the RCA indices requires trade data between all countries, we can only construct the RCA at the HS6 digit level, based on data from UN Comtrade.

Import demand elasticities Whether a specific good is chosen for retaliation may also depend on the associated (import) demand elasticities. Presumably, in order for retaliation to be effective, goods for which import-demand is found to be particularly price elastic would prove to be more effective. Further, tariffs on goods with a high import demand elasticity are less likely to affect domestic consumers. We, therefore, use the import-demand elasticity estimates constructed by [Soderbery \(2018\)](#) at the HS4 level for each of the retaliating countries. As before, we compute the retaliation-specific weighted average import-demand elasticity specific to a counterfactual retaliation list i for country r , $\sigma_{i,r}$ and evaluate this against the elasticities associated with the actually chosen retaliation response, σ_{r^*} .²⁰

Dominance of US exports Countries may also want to avoid retaliating and raising the cost of specific imports for which the US is the predominant source. To measure this, we construct the share of imports $I_{i,h,r}$ of a good h on a retaliation list i of country r that stems from the US relative to the rest of the world, $s_{h,i,r} = \frac{I_{i,h,r}}{\sum_c I_{h,c}}$. We compute the trade-volume weighted average implied share of US imports, $s_{i,r}$ for each good in the retaliation lists, across each of the counterfactual retaliation lists i for country r . We then again evaluate the corresponding shares associated

¹⁹While the sum of the weights across baskets will be the same as our counterfactual baskets target a similar volume of trade, the distribution of weights differ.

²⁰For the EU, we use Germany as the US's biggest trading partner's estimated elasticities from [Soderbery \(2018\)](#). The results qualitatively similar if we use other EU countries as reference.

with the actual retaliation list s_{r*} compared to the counterfactual lists. This analysis is conducted at the HS6 level (based on UN Comtrade data).

In Table 5, we report summary statistics for the three measures and how they compare across retaliation baskets. Ideally, countries, in order to minimise harm to their own economy, would favour retaliating against goods with a low RCA, a large import-demand elasticity and a low US import market share. In Table 6 we contrast how the distribution of counterfactual baskets compares with the actual retaliation response. The EU's retaliation appears to be targeting goods for which the US has a weaker RCA and goods for which US is a less dominant supplier. The Mexican response, on the other hand, appears to target goods with a relatively high import demand elasticity and a lower revealed comparative advantage.

We next shed light on the underlying trade-offs visually.

Results For every (potential) retaliation list i of retaliating country r , we have now constructed a vector of attributes $(\hat{\beta}_{i,r}, RCA_{i,r}, s_{i,r}, \sigma_{i,r})$. To illustrate the trade-offs and constraints imposed on retaliation design we visualise the joint distribution of the pair $(\hat{\beta}_{i,r}, RCA_{i,r})$ in Figure 4. The horizontal axis measures the degree of political targeting (measured by the changes in the Republican party vote share between 2012 and 2016). The vertical axis captures the different RCA index values. Conceptually, countries should aim to design retaliation in the bottom right corner as this would imply a high degree of political targeting, while at the same time, targeting goods with a low revealed comparative advantage.

The figure also highlights some of the specifics around the feasible counterfactual retaliation set. For China, there are very limited choices available to design a commensurate retaliation response (top-right corner). While there exists a broad

set of *feasible* retaliation bundles the vast majority of them would imply weak political targeting, even targeting countries that swung away from Trump. Among the few bundles with positive political targeting, the revealed comparative advantage measure for the US is high. This shows that the structure of US exports to China, which is concentrated in agricultural produce and high technology manufactured goods, implies significant constraints on the Chinese ability to retaliate.²¹ For the EU, Canada and Mexico, which share a much more diverse goods-trade relationships with the US, there are much fewer constraints on retaliation design. Relative to the counterfactual baskets, we observe that in particular for the EU and China, retaliation appears to have been chosen at the upper end. To the best of our knowledge, we are not aware of another paper that has explored retaliation in this way. For the EU, there exist very few alternative retaliation bundles that would produce a higher degree of political targeting and a lower RCA value. The same is true for Canada, and, to a lesser extent for Mexico.

In Appendix Figure A6, we study the implied import-demand elasticity. The figure highlights that, for both Canada and Mexico, retaliation appears to targeted towards goods with a high import demand elasticity and a higher degree of political targeting. Appendix Figure A7 studies the implied US market power for specific retaliation baskets. Based on this measure, the EU's retaliation response stands out in achieving a fair degree of political targeting, while avoiding goods for which the US is a dominant supplier.

In Table 7, we compute the shares of retaliation baskets that would imply a higher degree of political targeting while considering our other proxies capturing

²¹See Costa et al. (2016) for work on the impact of China's commodities-for-manufactures trade and Garred (2018) for China's trade policy post WTO accession.

retaliation effectiveness and domestic economic harm. Throughout, the chosen retaliation appears at the upper end in terms of producing high political targeting but a lower RCA. For the EU only around 1% of the counterfactual retaliation responses would produce a higher degree of political targeting and a lower RCA. The Chinese retaliation response clearly stands out as it appears to target goods with a high RCA. Much of this is afforded by the specific constraints that Chinese retaliation design faces as the vast majority of other feasible retaliation baskets would produce no political targeting whatsoever.

5 Conclusion

Based on the recent trade escalation provoked by the administration of Donald Trump, this paper provides empirical evidence for the political targeting of retaliatory tariffs. Using a novel simulation approach, we show that retaliatory tariffs indeed disproportionately targeted more Republican areas. This suggests that retaliatory tariffs appear to have a clear political dimension. We further illustrate that countries face a trade-off between the degree of political targeting and potential harm done their own economy. Our findings suggest that countries appear to put different weights on these two policy objectives. To the best of our knowledge, this paper is the first to empirically document this trade-off.

Future work should hence incorporate whether retaliation is effective in shaping the underlying trade-policy preferences of politicians and the electorate more broadly. This paper suggests that such an empirical study, for example, using difference-in-difference designs will have to find a way to navigate the endogeneity of retaliation exposure that this paper highlights.

References

- Ahn, D. P. and R. D. Ludema (2017). *Measuring Smartness: Understanding the Economic Impact of Targeted Sanctions*. United States Department of State.
- Alesina, A. and H. Rosenthal (1995). *Partisan Politics, Divided Government and the Economy*. Cambridge University Press.
- Alesina, A. and H. Rosenthal (2006). A Theory of Divided Government. *Econometrica* 64(6), 1311.
- Allen, S. H. (2008). The domestic political costs of economic sanctions. *Journal of Conflict Resolution* 52(6), 916–944.
- Amiti, M., S. Redding, and D. Weinstein (2019). The Impact of the 2018 Trade War on U.S. Prices and Welfare. Technical report, National Bureau of Economic Research, Cambridge, MA.
- Ansolabehere, S. and D. Rivers (2013). Cooperative Survey Research. *Annual Review of Political Science* 16(1), 307–329.
- Autor, D., D. Dorn, G. Hanson, and K. Majlesi (2016). Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. *CEPR Discussion Paper* 11511.
- Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China Syndrome: Local labor market impacts of import Competition in the United States. *American Economic Review* 103(6), 2121–2168.

- Baccini, L. (2010). Explaining formation and design of EU trade agreements: The role of transparency and flexibility. *European Union Politics* 11(2), 195–217.
- Baker, A. (2005). Who Wants to Globalize? Consumer Tastes and Labor Markets in a Theory of Trade Policy Beliefs. *American Journal of Political Science* 49(4), 924–938.
- Balassa, B. (1965). Trade Liberalisation and "Revealed" Comparative Advantage. *The Manchester School* 33(2), 99–123.
- Baldwin, R. E. (2004). Openness and Growth: What's the Empirical Relationship? In R. E. Baldwin and L. A. Winters (Eds.), *Challenges to Globalization: Analyzing the Economics*, Chapter 13.
- Barari, S., I. S. Kim, and W. Wong (2019). Trade Liberalization and Regime Type: Evidence from a New Tariff-line Dataset. *mimeo*.
- Berry, C. R., B. C. Burden, and W. G. Howell (2010). The president and the distribution of federal spending. *American Political Science Review* 104(4), 783–799.
- Bown, C. P. (2004). On the economic success of gatt/wto dispute settlement. *Review of Economics and statistics* 86(3), 811–823.
- Breuss, F. (2004). WTO Dispute Settlement: An Economic Analysis of Four EU US Mini Trade Wars. *Journal of Industry, Competition and Trade* 4(4), 275–315.
- Brookings (2017). Export Monitor. Technical report.
- Cameron, G. T. and P. Schuyler (2007). The political economy of international agricultural protection. *The Journal of Politics* 69(1), 116–127.

- Chan, S. P. and W. Smale (2018). Hit them in the harleys: Eu fights trump tariffs. *BBC*.
- Che, Y., Y. Lu, J. R. Pierce, P. K. Schott, and Z. Tao (2017). Did Trade Liberalization with China Influence U.S. Elections? *mimeo*.
- Colantone, I. and P. Stanig (2018a). Global Competition and Brexit. *American Political Science Review* 112(02), 201–218.
- Colantone, I. and P. Stanig (2018b). The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe. *American Journal of Political Science* 62(4), 936–953.
- Costa, F., J. Garred, and J. P. Pessoa (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics* 102, 50–69.
- DellaVigna, S. and E. Kaplan (2007). The fox news effect: Media bias and voting. *Quarterly Journal of Economics* 122(3), 1187–1234.
- Dippel, C., R. Gold, and S. Heblich (2015). Globalization and Its (Dis-)Content: Trade Shocks and Voting Behavior. *NBER Working Paper* 21812.
- Draca, M., J. Garred, L. Stickland, and N. Warrinnier (2018). On target? the incidence of sanctions across listed firms in iran. Technical report, Competitive Advantage in the Global Economy (CAGE).
- Eaton, J. and M. Engers (1992). Sanctions. *Journal of Political Economy* 100(5), 899–928.
- Elliott, K. A. and G. C. Hufbauer (1999). Same song, same refrain? economic sanctions in the 1990's. *American Economic Review* 89(2), 403–408.

- Enamorado, T. and K. Imai (2018). Validating Self-Reported Turnout by Linking Public Opinion Surveys with Administrative Records. *SSRN Electronic Journal*.
- Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2020). The Return to Protectionism. *The Quarterly Journal of Economics* 135(1), 1–55.
- Feigenbaum, J. J. and A. B. Hall (2015). How legislators respond to localized economic shocks: Evidence from Chinese import competition. *Journal of Politics* 77(4), 1012–1030.
- Frankel, J. A. and D. H. Romer (1999). Does trade cause growth? *American Economic Review* 89(3), 379–399.
- Garred, J. (2018). The persistence of trade policy in China after WTO accession. *Journal of International Economics* 114, 130–142.
- Gawande, K. and W. L. Hansen (1999). Retaliation, bargaining, and the pursuit of “free and fair” trade. *International Organization* 53(1), 117–159.
- Grossman, G. M. and E. Helpman (1994). Protection for sale. *American Economic Review* 84(4), 833–850.
- Guiso, L., H. Herrera, M. Morelli, and T. Sonno (2018). Populism: Demand and Supply. *Mimeo*, 1–63.
- Hansen, J. M. (1990). Taxation and the political economy of the tariff. *International Organization* 44(4), 527–551.
- Heckscher, E. and B. Ohlin (1933). Interregional and international trade. *Harvard University Press, Cambridge, MA*.

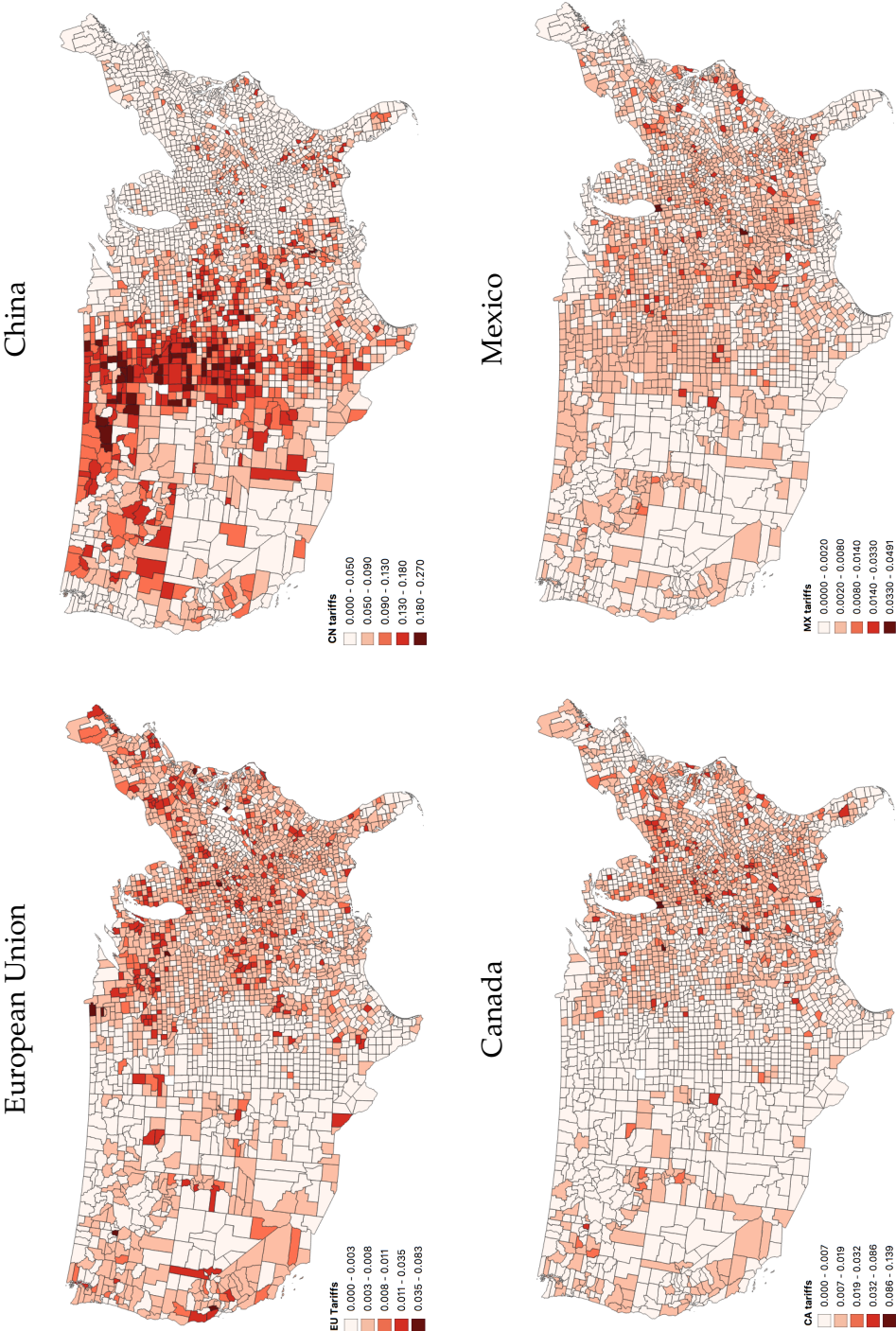
- Irwin, D. A. (1998). The Smoot-Hawley Tariff: A Quantitative Assessment. *Review of Economics and Statistics* 80(2), 326–334.
- Kavaklı, K. C., J. T. Chatagnier, and E. Hatipoglu (2020). The Power to Hurt and the Effectiveness of International Sanctions. *Journal of Politics* 82(3), 897–894.
- Kono, D. Y. (2006). Optimal Obfuscation : Democracy and Trade Policy Transparency. *American Political Science Review* 100(3), 369–384.
- Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review* 103(5), 1960–1976.
- Levendusky, M. S. (2013). Why do partisan media polarize viewers? *American Journal of Political Science* 57(3), 611–623.
- Levitt, S. D. and J. M. Snyder (1995). Political parties and the distribution of federal outlays. *American Journal of Political Science* 39(4), 958–980.
- Lü, X., K. Scheve, and M. J. Slaughter (2012). Inequity Aversion and the International Distribution of Trade Protection. *American Journal of Political Science* 56(3), 638–654.
- Madestam, A., D. Shoag, S. Veuger, and D. Yanagizawa-Drott (2013). Do Political Protests Work? Evidence from the Tea Party Movement. *The Quarterly Journal of Economics*, 1633–1685.
- Marinov, N. (2005). Do economic sanctions destabilize country leaders? *American Journal of Political Science* 49(3), 564–576.
- Martin, G. J. and S. W. Webster (2018). Does residential sorting explain geographic polarization? *Political Science Research and Methods*.

- McCarty, N., K. T. Poole, and H. Rosenthal (2009). Does Gerrymandering Cause Polarization? *American Journal of Political Science* 53(9).
- NYT (2018). To ease pain of trump's trade war: Usd 12 billion in aid for farmers. <https://www.nytimes.com/2018/07/24/us/politics/farmers-aid-trade-war.html>.
- Ricardo, D. (1891). *Principles of political economy and taxation*. G. Bell.
- Rosendorff, B. P. (2005). Stability and Rigidity: The Dispute Settlement Procedure of the WTO's Dispute Settlement Procedure. *American Political Science Review* 99(3), 389–400.
- Sattler, T., G. Spilker, and T. Bernauer (2014). Does WTO Dispute Settlement Enforce or Inform? *British Journal of Political Science* 44(4), 877–902.
- Scheve, K. and M. J. Slaughter (2004). Economic Insecurity and the Globalization of Production. *American Journal of Political Science* 48(4), 662–674.
- Scheve, K. and M. Tomz (1999). Electoral surprise and the midterm loss in US congressional elections. *British Journal of Political Science* 29(3), 507–521.
- Scheve, K. F. and M. J. Slaughter (2001). What determines individual trade-policy preferences? *Journal of International Economics* 54(2), 267–292.
- Schott, P. K. (2008). The relative sophistication of Chinese exports. In *Economic Policy*, Volume 23, pp. 5–49.
- Soderbery, A. (2018). Trade elasticities, heterogeneity, and optimal tariffs. *Journal of International Economics* 114, 44–62.

Stasavage, D. (2004). Open-Door or Closed-Door? Transparency in Domestic and International Bargaining. *International Organization* 58(4), 667–703.

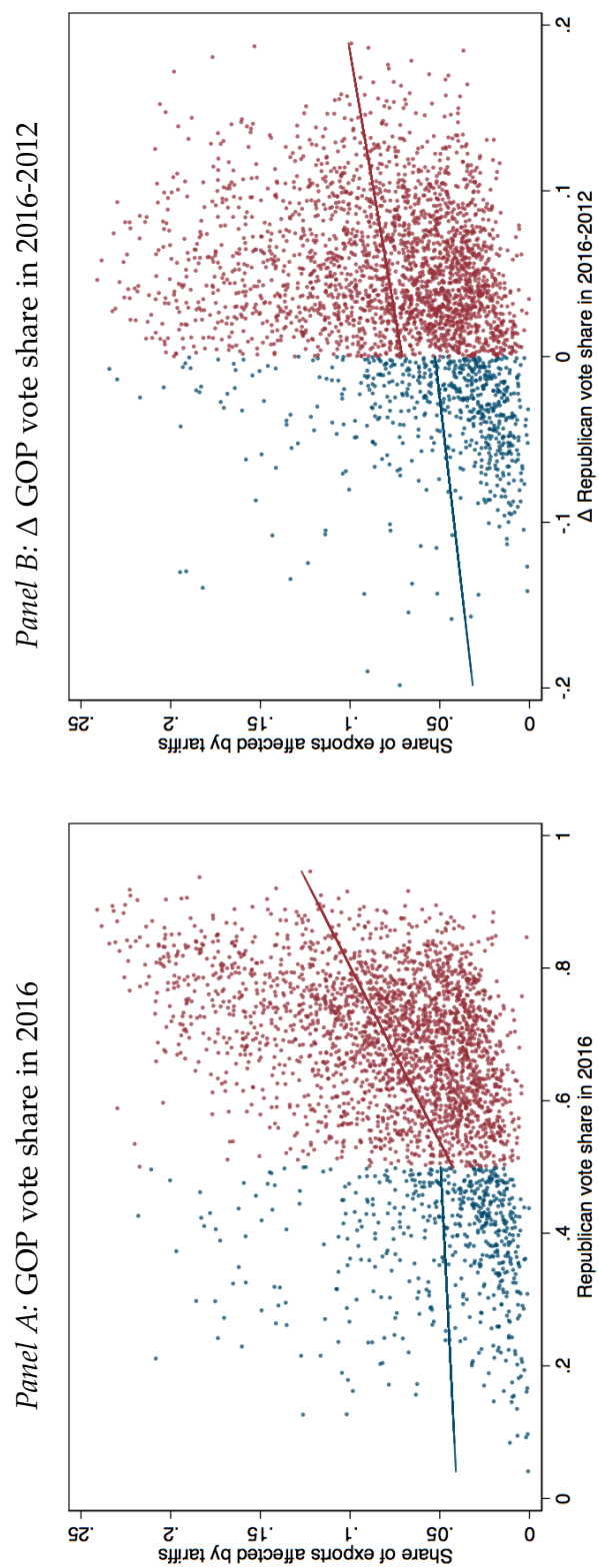
Williamson, V., T. Skocpol, and J. Coggin (2011). The tea party and the remaking of Republican conservatism. *Perspectives on Politics* 9(1), 25–43.

Figure 1: Distribution of share of county level export trade volumes affected by retaliation measures by the EU, China, Canada and Mexico



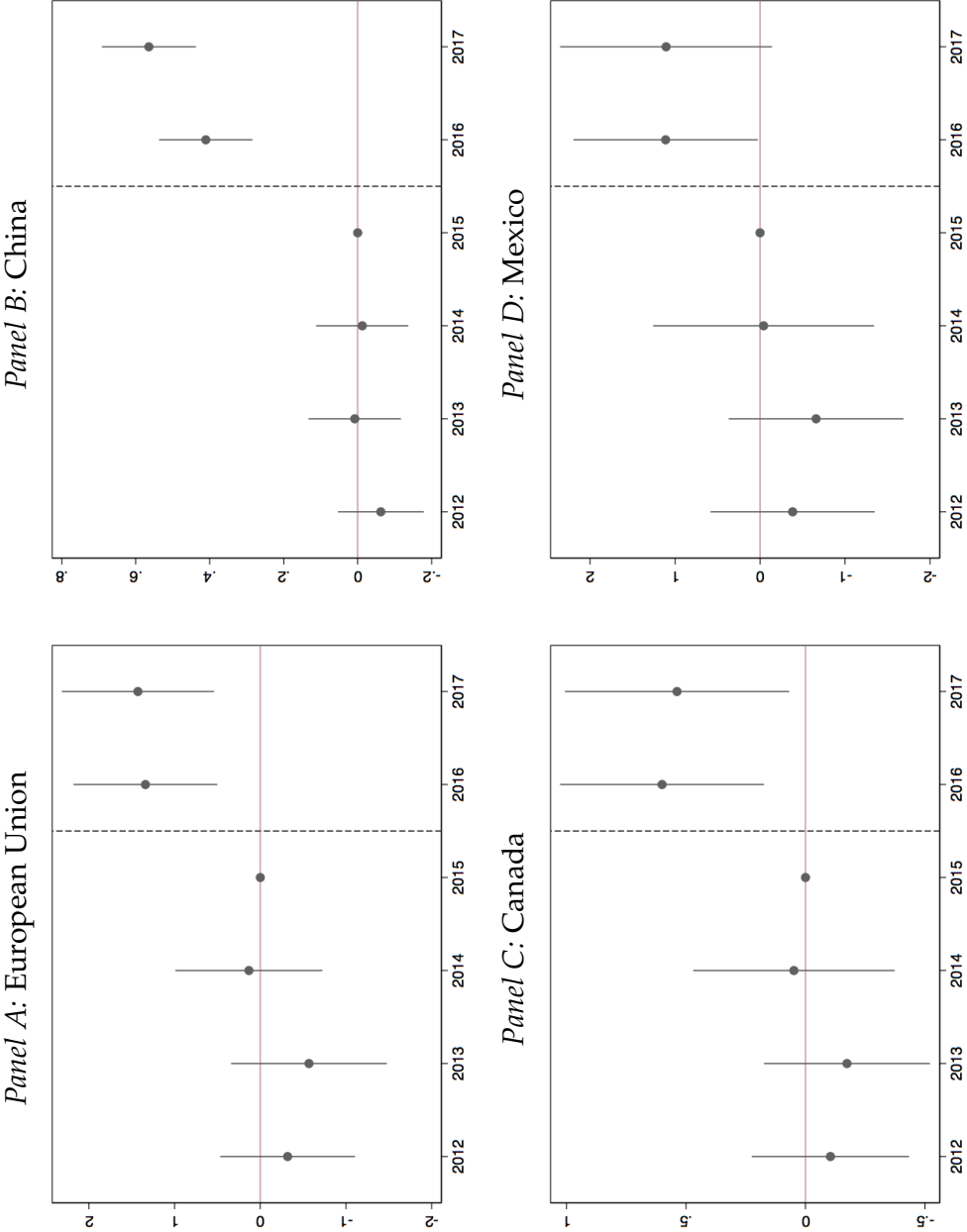
Notes: Map plots the quintiles of the county level exposure measure to retaliation from the respective countries. The construction of the exposure measure is described in more detail in Section 2.3.

Figure 2: County level export share exposed to tariffs and Republican Vote Share



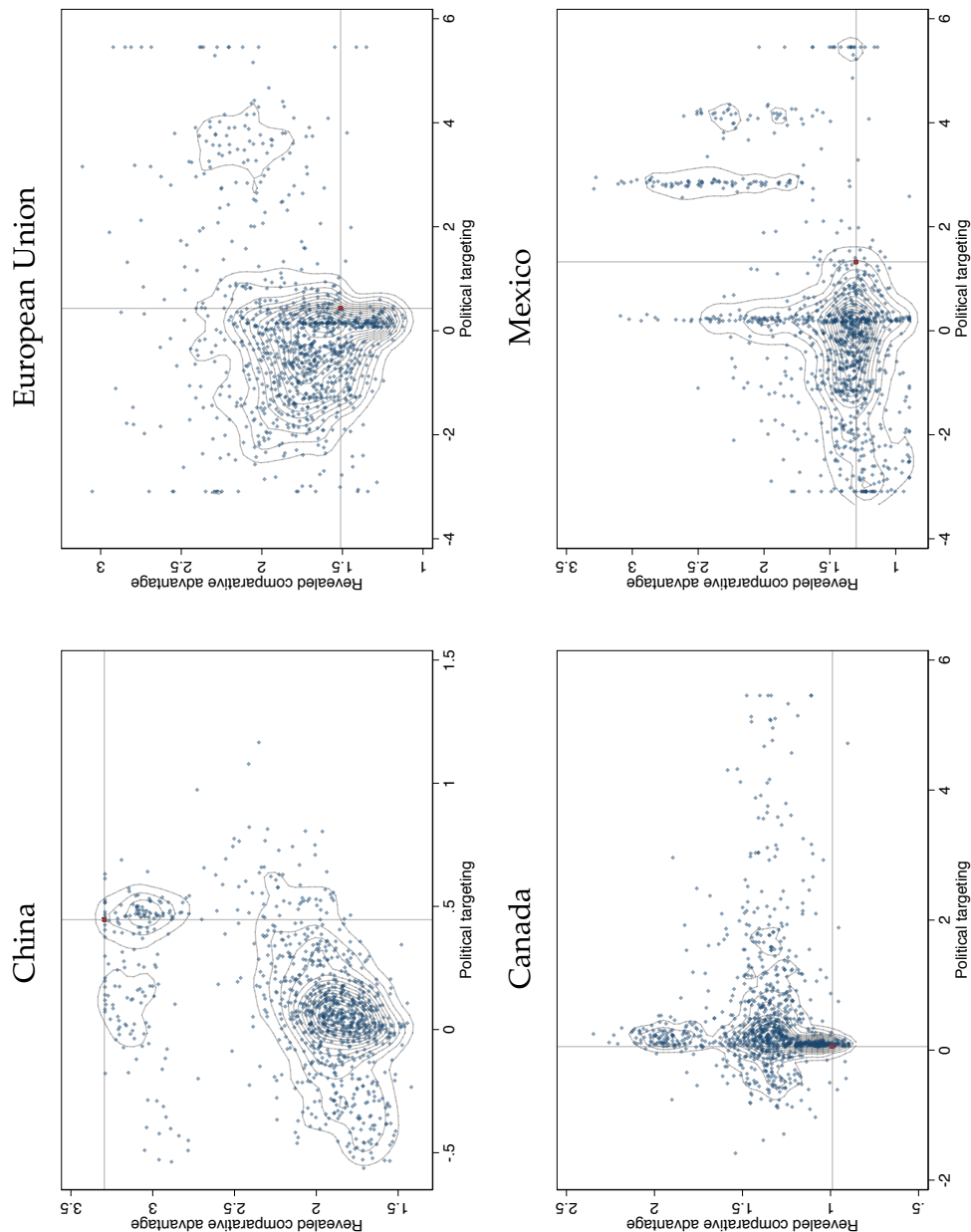
Notes: Figure plots the Republican party vote share in the 2016 Presidential election on the horizontal axis in Panel A and the change in the Republican party vote shares between the 2016 and 2012 Presidential elections at the county level in Panel B against the overall share of a county's exports that are exposed to retaliation by all countries.

Figure 3: Was retaliation targeted? Evidence from individual-level republican party affiliation and county level exposure to retaliatory tariffs



Notes: Figure plots regression results capturing how the strength of the correlation between individual-level republican party affiliation and the county-level retaliation exposure measure evolved over time across the Gallup samples. Throughout it appears that the correlation becomes markedly stronger from 2016 suggesting that retaliation was targeted towards areas with resident respondents who identify with the Republican party under Donald Trump from 2016 onwards. The omitted year is 2015. All regressions control for county fixed effects, year-effects as well as indicators for race, gender and income across 12 categories. 90% confidence intervals obtained from clustering standard errors at the county level are indicated. Observations are weighted using the provided survey weights.

Figure 4: Trade-off in political targeting and revealed comparative advantage of US: Δ GOP vote share 2012-2016.



Notes: Figure plots bivariate kernel densities of the joint distribution the two measures across the 1000 simulated retaliation baskets. The vertical axis presents the revealed comparative advantage index, while the horizontal axis displays the degree of political targeting. Areas in the lower right corner indicate high degrees of political targeting of an specific retaliation basket and lower revealed comparative advantage. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Table 1: Measuring degree of political targeting of retaliation measure studying GOP electoral performance in 2016

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: 2016 GOP vote share</i>					
Retaliation exposure	2.459*** (0.233)	3.083*** (0.209)	7.773*** (1.508)	2.314** (1.120)	7.869** (3.815)
Observations	3104	3104	3104	3104	3104
Clusters	3104	3104	3104	3104	3104
Mean of DV	.458	.458	.458	.458	.458
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel B: Δ GOP vote share 2016-2012</i>					
Retaliation exposure	0.750*** (0.054)	0.891*** (0.057)	2.598*** (0.368)	0.880*** (0.239)	2.885*** (0.833)
Observations	3063	3063	3063	3063	3063
Clusters	3063	3063	3063	3063	3063
Mean of DV	-.0137	-.0137	-.0137	-.0137	-.0137
State FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A or the change in republican party vote share between 2016 and 2012 in Panel B. All regressions include state fixed effects. Counties are weighted by the county-level population. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Measuring degree of political targeting using individual-level data from 2016 and 2017

	(1)	(2)	(3)	(4)	(5)
	Retaliatory tariffs imposed by...				
	Combined	CN	EU	CA	MX
<i>Panel A: Self-identified republican</i>					
Retaliation exposure	1.185*** (0.114)	1.423*** (0.107)	3.799*** (0.828)	1.225** (0.572)	3.938** (1.798)
Observations	376620	376620	376620	376620	376620
Counties	2956	2956	2956	2956	2956
Mean of DV	.421	.421	.421	.421	.421
<i>Panel B: Favorable view of Trump (candidate)</i>					
Retaliation exposure	0.629*** (0.062)	0.738*** (0.080)	2.100*** (0.500)	0.533*** (0.181)	1.902*** (0.537)
Observations	111152	111152	111152	111152	111152
Counties	2817	2817	2817	2817	2817
Mean of DV	.335	.335	.335	.335	.335
GOP Party identification	Yes	Yes	Yes	Yes	Yes
<i>Panel C: Presidential approval for Trump</i>					
Retaliation exposure	0.733*** (0.067)	0.909*** (0.065)	1.535*** (0.463)	0.651** (0.293)	2.300** (0.989)
Observations	181504	181504	181504	181504	181504
Counties	2876	2876	2876	2876	2876
Mean of DV	.412	.412	.412	.412	.412
GOP Party identification	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable indicating in Panel A whether a respondent is a republican or leaning to republican; whether the respondent holds a favorable view of Donald Trump as a Presidential candidate in Panel B asked from July 2015 until October 2016; or whether they approve of Donald Trump's performance as President asked from January 2017 until mid 2018. The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. Observations are weighted by the provided survey weights. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Measuring degree of political targeting: exploiting individual-level within 2016 Republican Party Presidential candidate variation from June 2015 to March 2016

	(1)	(2)	(3)	(4)	(5)
	Retaliatory tariffs imposed by...				
<i>DV: Favorable view of...</i>	Combined	CN	EU	CA	MX
<i>Panel A: Donald Trump</i>					
Retaliation exposure	0.658*** (0.177)	0.670*** (0.203)	3.559** (1.405)	0.693 (0.864)	3.565 (2.220)
Observations	12806	12806	12806	12806	12806
Counties	2035	2035	2035	2035	2035
Mean of DV	.591	.591	.591	.591	.591
<i>Panel B: Ted Cruz</i>					
Retaliation exposure	0.199 (0.151)	0.174 (0.187)	0.575 (1.373)	0.897* (0.497)	1.352 (1.335)
Observations	12998	12998	12998	12998	12998
Counties	2051	2051	2051	2051	2051
Mean of DV	.569	.569	.569	.569	.569
<i>Panel C: Marc Rubio</i>					
Retaliation exposure	-0.537*** (0.188)	-0.659*** (0.216)	-0.234 (1.429)	0.088 (0.781)	-1.771 (2.527)
Observations	11554	11554	11554	11554	11554
Counties	2023	2023	2023	2023	2023
Mean of DV	.588	.588	.588	.588	.588
<i>Panel D: John Kasich</i>					
Retaliation exposure	-0.650*** (0.153)	-0.860*** (0.164)	-1.835 (1.187)	0.135 (0.583)	-1.086 (1.852)
Observations	13071	13071	13071	13071	13071
Counties	2050	2050	2050	2050	2050
Mean of DV	.376	.376	.376	.376	.376
Sample	Self-identifying Republicans				
State FE	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator stating whether a respondent holds a favorable view of the candidate indicated. The responses includes don't know, refused and those that hold no view. The patterns are robust to dropping these observations. Regressions include individual level controls: respondents racial identity, income, republican party affiliation, gender and the year of the survey. Regressions are weighted using survey weights provided by Gallup. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Evaluation of actual retaliation response relative to counterfactual retaliation: evaluating political targeting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	County level		Gallup capturing Trump		CCES Trump		
	GOP_{2016}	ΔGOP_{2016}^{2012}	Favorable View	Approval	Vote	Switched to	Obama to Trump
$\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*})$							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.351	0.203	0.240	0.280	0.220	0.188	0.212
CA	0.940	0.811	0.650	0.760	0.780	0.800	0.768
MX	0.257	0.172	0.520	0.580	0.512	0.552	0.476

Notes: The table reports analysis of the implied measures of the extent of political targeting implied by the set of simulated counterfactual retaliation baskets vis-a-vis the actually chosen retaliation response. The figures represent the share of retaliation baskets that imply a retaliation exposure measure above what is implied in the actually chosen retaliation response. Columns (1) - (2) study the county level data explored in Table 1, columns (3) - (5) use the measures leveraged in Table 2, while columns (6)-(8) explore the measures studied in Table A10.

Table 5: Summary statistics of counterfactual retaliation baskets vis-a-vis actual retaliation response

	Retaliatory tariffs imposed by...							
	CN		EU		CA		MX	
	Mean (SD)	Actual r*	Mean (SD)	Actual r*	Mean (SD)	Actual r*	Mean (SD)	Actual r*
$RCA_{i,r}$	2.101 0.484	3.296	1.788 0.335	1.511	1.373 0.260	0.990	1.524 0.441	1.301
Import demand elasticity $\sigma_{i,r}$	3.845 0.346	4.384	3.178 0.179	3.070	3.834 0.387	3.886	3.115 0.836	3.348
US import market share $s_{i,r}$	0.226 0.042	0.369	0.158 0.071	0.132	0.668 0.041	0.760	0.690 0.121	0.723

Notes: The table presents summary statistics of the other measures constructed for the counterfactual retaliation baskets along with the measure for the actually implemented retaliation basket.

Table 6: Retaliation design-trade offs

	(1)	(2)	(3)	(4)
	CN	EU	CA	MX
Share of retaliation bundles with...				
$\Pr(RCA_{i,r} < RCA_{r^*})$	0.982	0.198	0.036	0.331
Import demand elasticity $\Pr(\sigma_{i,r} > \sigma_{r^*})$	0.059	0.686	0.599	0.073
US import market share $\Pr(s_{i,r} < s_{r^*})$	1.000	0.459	0.996	0.564

Notes: Table evaluates the further measures associated with counterfactual retaliation responses against the measure associated with the actual retaliation chosen. The figures compute the share of counterfactual baskets above or below the value associated with the actual retaliation response.

Table 7: Trade-offs and targeting in retaliation design: evidence from counterfactual retaliation responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	County level		Gallup capturing Trump		CCES Trump		
	GOP_{2016}	ΔGOP_{2012}^{2016}	Fav. View	Approval	Vote	Switched to	Obama to Trump
<i>Panel A: $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*})$</i>							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.351	0.203	0.240	0.280	0.220	0.188	0.212
CA	0.940	0.811	0.650	0.760	0.780	0.800	0.768
MX	0.257	0.172	0.520	0.580	0.512	0.552	0.476
<i>Panel B: $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap RCA_{i,r} < RCA_{r^*})$</i>							
CN	0.206	0.122	0.050	0.060	0.044	0.052	0.052
EU	0.043	0.008	0.010	0.010	0.016	0.008	0.012
CA	0.035	0.033	0.010	0.020	0.020	0.032	0.036
MX	0.052	0.014	0.160	0.180	0.132	0.164	0.120
<i>Panel C: $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap \sigma_{i,r} > \sigma_{r^*})$</i>							
CN	0.020	0.013	0.020	0.020	0.016	0.016	0.016
EU	0.254	0.147	0.170	0.210	0.148	0.128	0.148
CA	0.570	0.494	0.420	0.500	0.456	0.460	0.440
MX	0.010	0.011	0.010	0.010	0.012	0.012	0.008
<i>Panel D: $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap s_{i,r} < s_{r^*})$</i>							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.139	0.070	0.110	0.130	0.084	0.076	0.088
CA	0.936	0.807	0.650	0.760	0.780	0.800	0.768
MX	0.119	0.062	0.280	0.340	0.268	0.244	0.172

Notes: The table reports analysis of the implied measures of the extent of political targeting implied by the set of simulated counterfactual retaliation baskets vis-a-vis the actually chosen retaliation response. The figures represent the share of retaliation baskets that imply a retaliation exposure measure above what is implied in the actually chosen retaliation response. Columns (1) - (2) study the county level data explored in Table 1, columns (3) - (5) use the measures leveraged in Table 2, while columns (6)-(8) explore the measures studied in Table A10.

Online Appendix

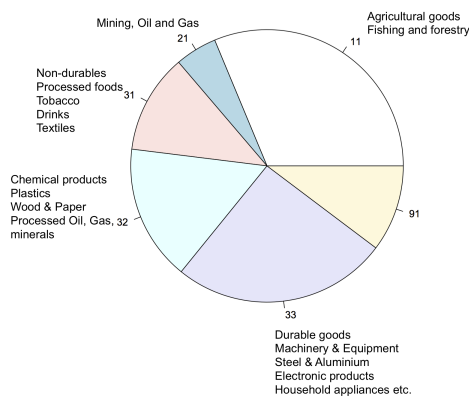
“Tariffs and Politics: Evidence from Trump’s Trade Wars”

For Online Publication

August 2020

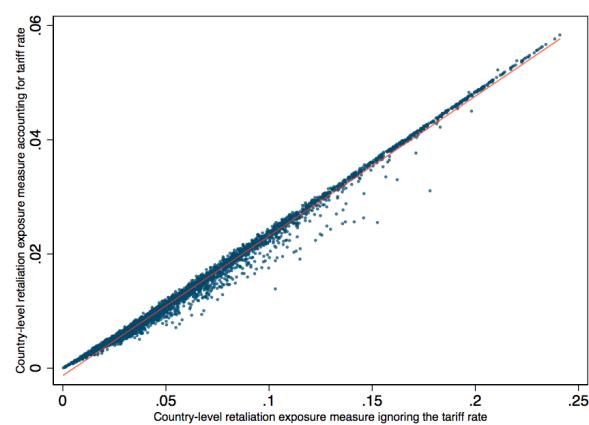
1 Additional Figures and Tables

Figure A1: Which sectors were targeted by retaliation measures? Combining the EU, Canada, Turkey, India, and Chinese retaliation lists.



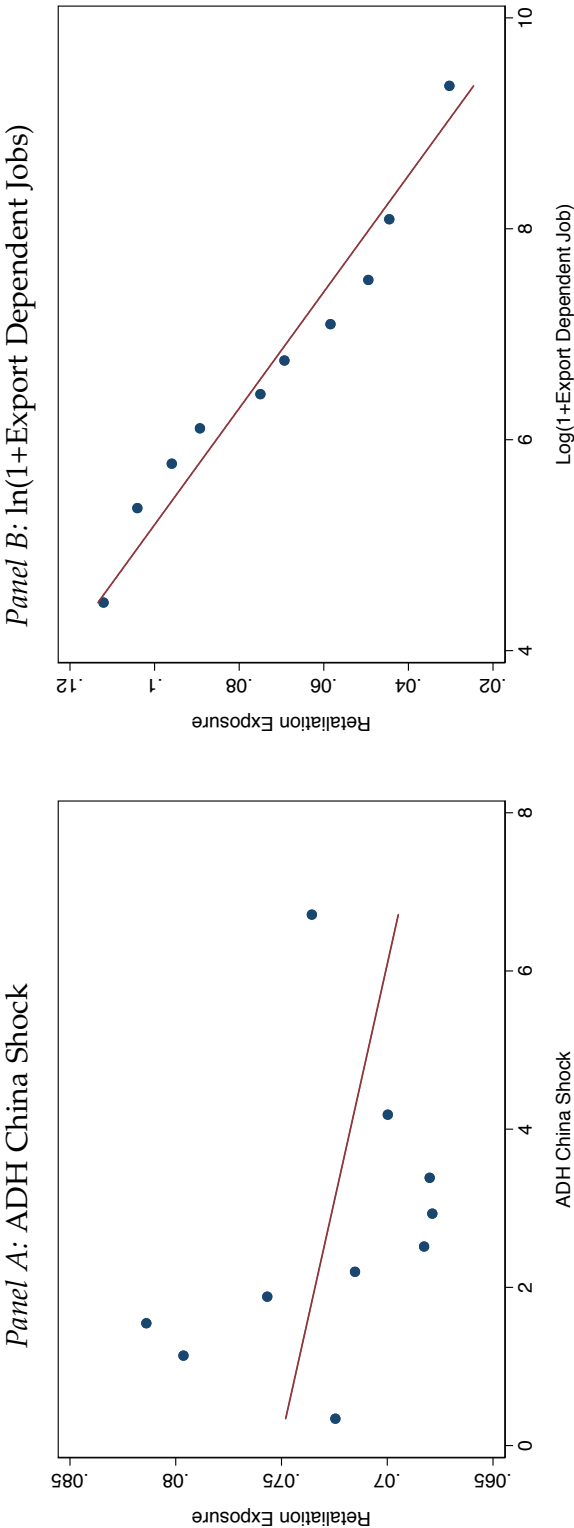
Notes: The pie chart plots the trade-volume weighted distribution of countermeasures across sectors using the 2017 export volume.

Figure A2: Ignoring tariff-rate does not skew retaliation exposure measure: comparing retaliation exposure measure including or ignoring the applied tariff rate



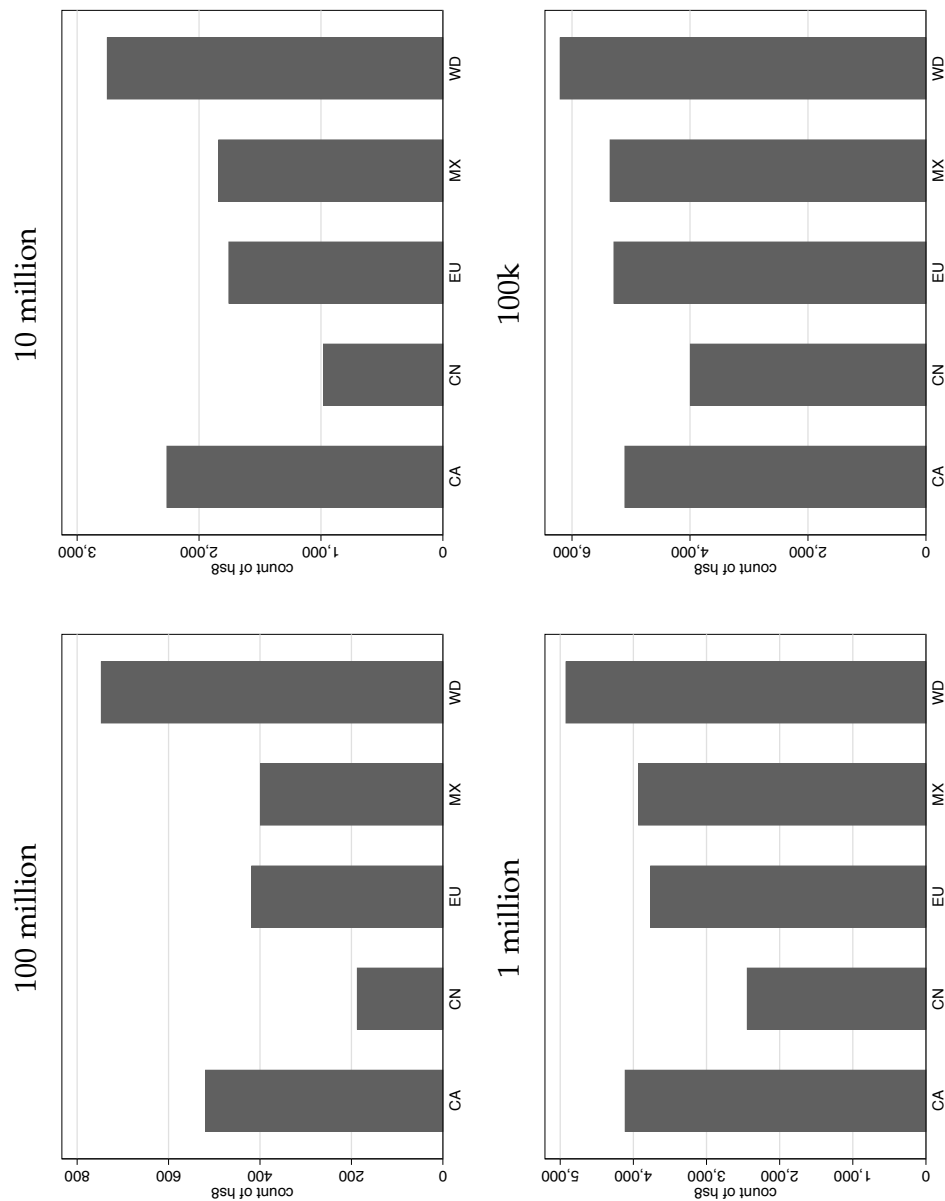
Notes: Figure plots the county level exposure measure including and excluding the actual tariff rate. The construction of the exposure measure is described in more detail in Section 2.3.

Figure A3: Retaliatory tariff exposure and Openness to Trade



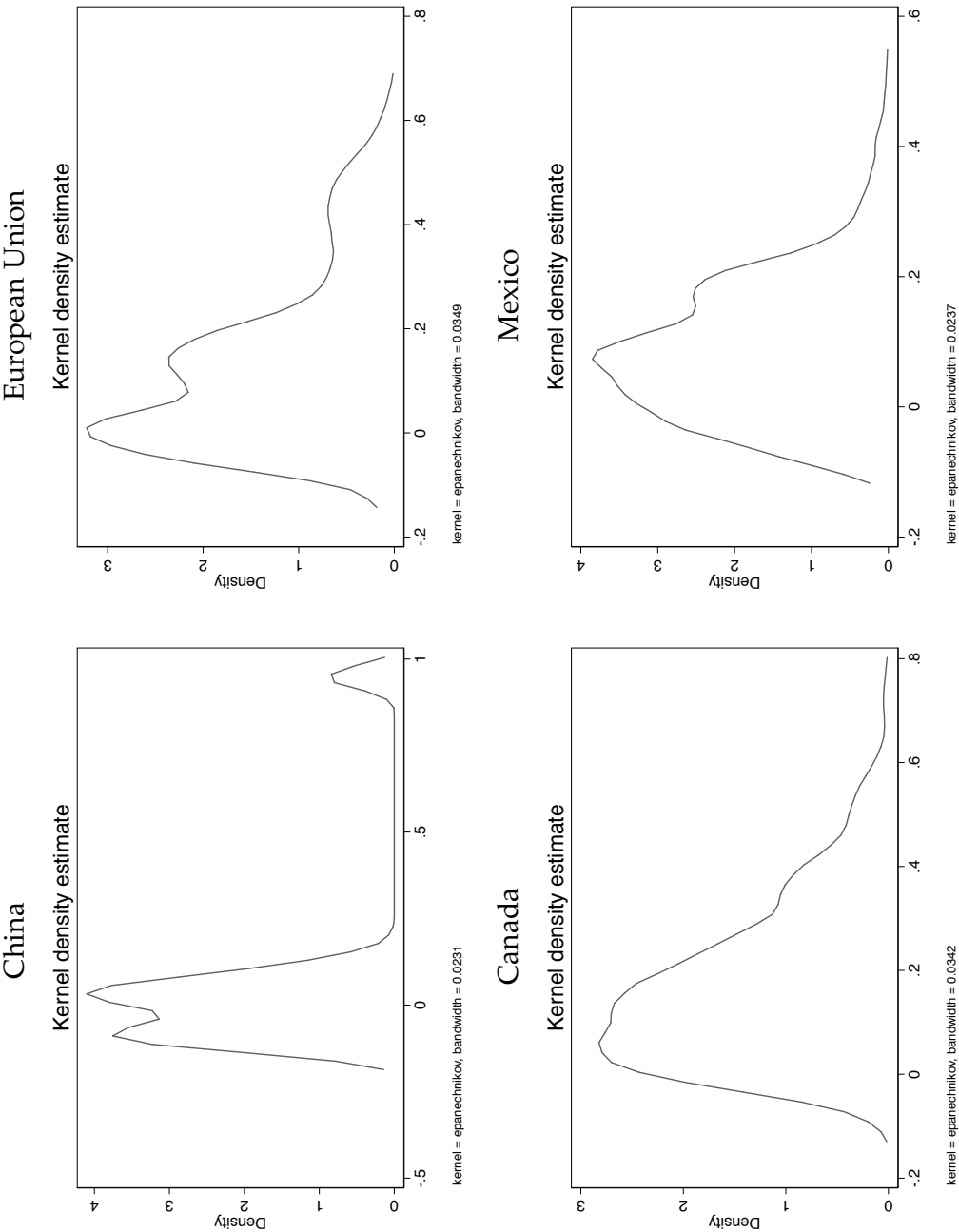
Notes: Figure plots binned scatter plots for the relationship of our retaliation exposure measure and the ADH China Shock (Panel A) or the number of export dependent jobs (Panel B).

Figure A4: Potential set of commodities that could be chosen for retaliation: Number of HS8 codes where US exports are above certain size thresholds - in total the data includes 7193 unique HS8 codes



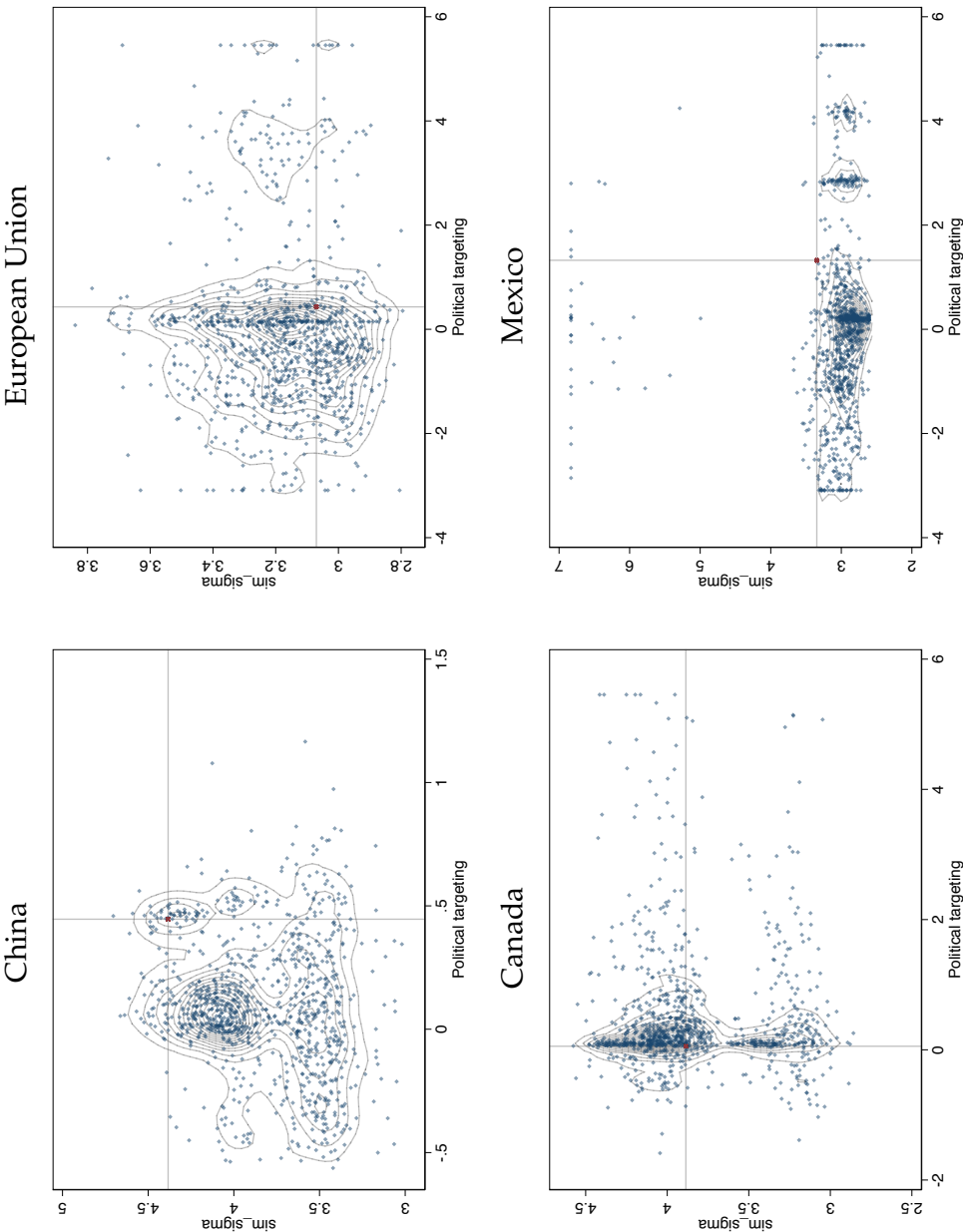
Notes: Figure plots distribution of unique number of HS8 codes on which the US is exporting more than 100, 10, 1 and 0.1 million USD worth of goods in 2017. This is an indication as to how rich or unconstrained the retaliation response can be designed.

Figure A5: Cross-correlation between actual retaliation exposure measure and counterfactual retaliation exposure measures across the different countries



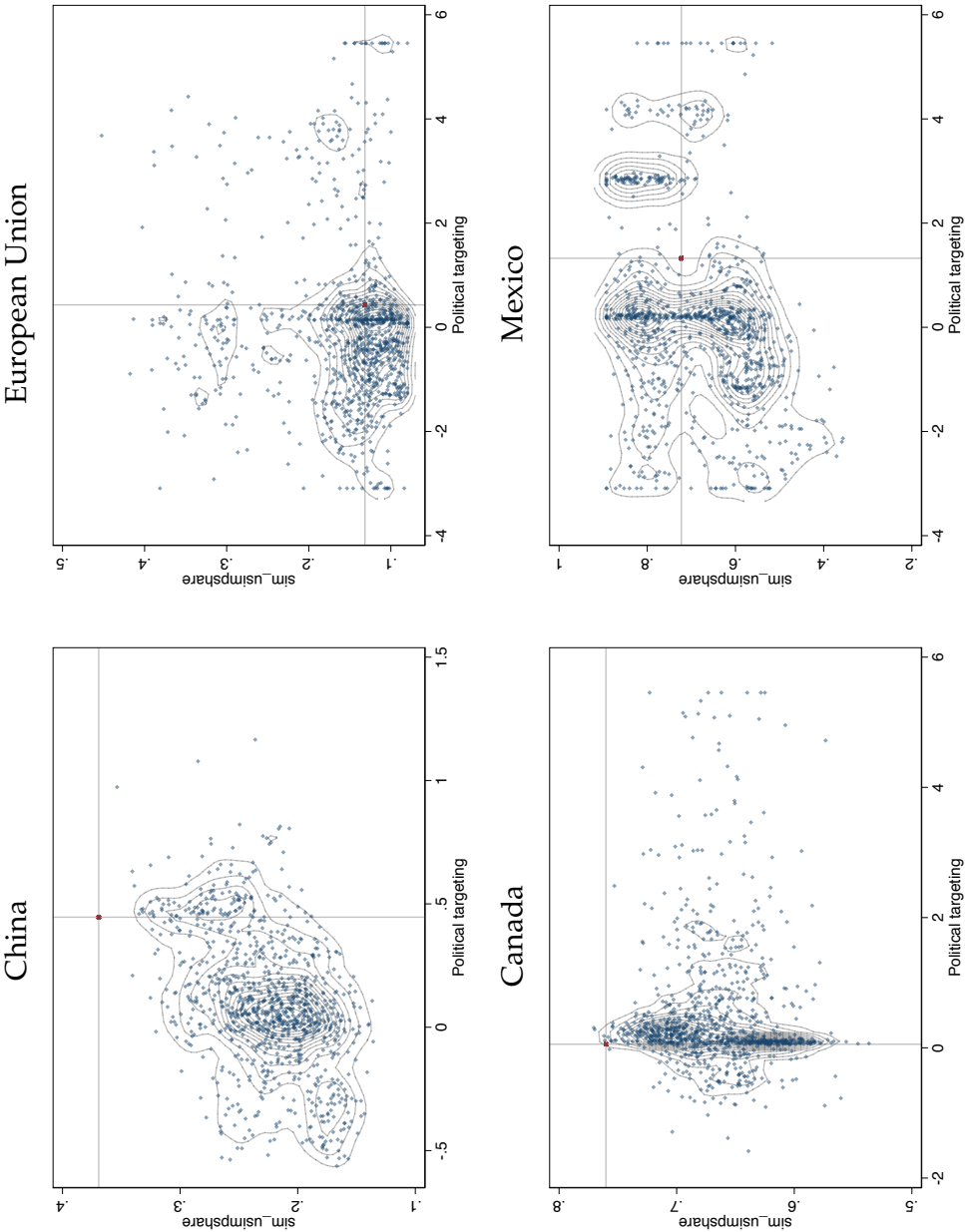
Notes: Figure plots the distribution of the correlation coefficient between the $\tau_{c,i}$ and the vector of 1000 $\tau_{c,i}$ associated with the alternative retaliation list. This highlights a non-negligible mechanically positive cross-correlation.

Figure A6: Trade-off between political targeting and implied import-demand elasticity of import basket: Δ GOP vote share 2012-2016.



Notes: Figure plots the bivariate joint distribution of the implied trade-weighted import-demand elasticities $\sigma_{i,r}$ and the measured degree of political targeting associated with the $\tau_{i,r}$ measures and the change in the Republican party vote share between 2012 and 2016. Each dot refers to one of the simulated retaliation baskets. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Figure A7: Trade-off between political targeting and share of US import's among all imports: Δ GOP vote share 2012-2016.



Notes: Figure plots the bivariate joint distribution of the implied trade-weighted US import share to retaliating countries $s_{i,r}$ and the measured degree of political targeting associated with the $\tau_{i,r}$ measures and the change in the Republican party vote share between 2012 and 2016. Each dot refers to one of the simulated retaliation baskets. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Table A1: Robustness of degree of political targeting of retaliation: using a sector-level employment based tariff exposure measure and GOP electoral performance in previous Presidential elections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Combined			China			European Union			Canada			Mexico		
	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008
<i>Panel A: GOP vote share</i>															
Retaliation exposure (CBP)	1.068*** (0.069)	0.780*** (0.062)	0.712*** (0.058)	1.057*** (0.083)	0.773*** (0.076)	0.713*** (0.070)	1.224*** (0.142)	0.906*** (0.108)	0.836*** (0.099)	1.120*** (0.092)	0.816*** (0.075)	0.765*** (0.069)	0.984*** (0.102)	0.757*** (0.084)	0.719*** (0.079)
Observations	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063
States	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063
Mean of DV	.458	.473	.459	.458	.473	.459	.458	.473	.459	.458	.473	.459	.458	.473	.459
<i>Panel B: Δ GOP vote share</i>															
Retaliation exposure (CBP)	0.297*** (0.018)	0.069*** (0.009)	0.088*** (0.013)	0.277*** (0.022)	0.060*** (0.010)	0.086*** (0.016)	0.391*** (0.038)	0.070*** (0.014)	0.094*** (0.022)	0.339*** (0.024)	0.052*** (0.010)	0.080*** (0.016)	0.275*** (0.024)	0.038*** (0.010)	0.064*** (0.017)
Observations	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063
States	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063
Mean of DV	-.0137	.0145	-.0522	-.0137	.0145	-.0522	-.0137	.0145	-.0522	-.0137	.0145	-.0522	-.0137	.0145	-.0522
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in Panel A or the change in republican party vote share between consecutive presidential elections in Panel B. The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. All regressions include state fixed effects. Counties are weighted by their population. Standard errors are clustered at the state level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Retaliation Exposure Measure Normalized by Population

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: 2016 GOP vote share</i>					
Retaliation exposure	272.747*** (57.549)	503.665*** (82.519)	375.730** (177.627)	121.295 (124.816)	571.138 (436.293)
Observations	3104	3104	3104	3104	3104
Clusters	48	48	48	48	48
Mean of DV	.458	.458	.458	.458	.458
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel B: Δ GOP vote share 2016-2012</i>					
Retaliation exposure	80.518*** (13.049)	129.577*** (27.286)	119.585*** (37.899)	58.892*** (21.026)	243.897** (92.895)
Observations	3063	3063	3063	3063	3063
Clusters	48	48	48	48	48
Mean of DV	-.0137	-.0137	-.0137	-.0137	-.0137
State FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A or the change in republican party vote share between 2016 and 2012 in Panel B. All regressions include state fixed effects. Counties are weighted by the county-level population. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Comparing degree of political targeting exploring GOP performance across *election types*

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: GOP 2016 vote share</i>					
President \times Retaliation exposure	2.459*** (0.233)	3.083*** (0.209)	7.773*** (1.508)	2.314** (1.120)	7.869** (3.816)
House \times Retaliation exposure	2.358*** (0.356)	3.105*** (0.269)	7.919*** (1.855)	1.477 (1.833)	5.054 (5.787)
Senate \times Retaliation exposure	1.344*** (0.211)	1.763*** (0.192)	6.019*** (1.572)	0.911 (0.862)	3.400 (2.779)
Observations	8085	8085	8085	8085	8085
Counties	3104	3104	3104	3104	3104
Mean of DV	.453	.453	.453	.453	.453
<i>Panel B: Δ GOP 2016 to 2012</i>					
President \times Retaliation exposure	0.750*** (0.054)	0.891*** (0.057)	2.598*** (0.368)	0.880*** (0.239)	2.885*** (0.834)
House \times Retaliation exposure	0.491*** (0.156)	0.715*** (0.113)	1.278* (0.769)	-0.105 (0.823)	-0.433 (2.448)
Senate \times Retaliation exposure	-0.368 (0.237)	-0.581* (0.346)	-0.115 (1.153)	-0.262 (0.268)	-1.000 (0.731)
Observations	6876	6876	6876	6876	6876
Counties	3063	3063	3063	3063	3063
Mean of DV	-.0116	-.0116	-.0116	-.0116	-.0116
State by Election Type FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A, the change in republican party vote share between 2016 and the most recent comparable election (2012 for Presidential election, 2014 for House Elections and various for Senate) in Panel B and the change in republican party vote share between 2016 and the 2012 Presidential election or the 2012 House or Senate elections (if applicable). All regressions include state by election type fixed effects. Counties are weighted by the county-level population. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Alternative Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Clustered Standard Errors			Conley Standard Errors		
	County	Commuting Zone	State	100km	500km	1000km
<i>Panel A: 2016 GOP vote share</i>						
Retaliation exposure	2.459*** (0.233)	2.459*** (0.264)	2.459*** (0.349)	2.459*** (0.235)	2.459*** (0.297)	2.459*** (0.295)
Observations	3104	3104	3104	3.03e+08	3.03e+08	3.03e+08
Clusters	3104	691	48			
Mean of DV	.458	.458	.458	.632	.632	.632
	Clustered Standard Errors			Conley Standard Errors		
	County	Commuting Zone	State	100km	500km	1000km
<i>Panel B: Δ GOP vote share 2016-2012</i>						
Retaliation exposure	0.750*** (0.054)	0.750*** (0.070)	0.750*** (0.125)	0.750*** (0.068)	0.750*** (0.125)	0.750*** (0.158)
Observations	3063	3063	3063	2.99e+08	2.99e+08	2.99e+08
Clusters	3063	691	48			
Mean of DV	-.0137	-.0137	-.0137	.0355	.0355	.0355
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A or the change in republican party vote share between 2016 and 2012 in Panel B. All regressions include state fixed effects. Counties are weighted by the county-level population. Standard errors are indicated on top of each column and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Robustness of degree of political targeting of retaliation: studying GOP electoral performance in previous Presidential elections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Combined			China			European Union			Canada			Mexico		
	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008
<i>Panel A: GOP vote share</i>															
Retaliation exposure	2.459*** (0.233)	1.714*** (0.209)	1.571*** (0.186)	3.083*** (0.209)	2.159*** (0.193)	1.956*** (0.177)	7.773*** (1.508)	5.990*** (1.356)	5.607*** (1.256)	2.314** (1.120)	1.548 (0.971)	1.610* (0.887)	7.869** (3.815)	5.008 (3.099)	5.021* (2.808)
Observations	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063
States	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063	3104	3063	3063
Mean of DV	.458	.473	.459	.458	.473	.459	.458	.473	.459	.458	.473	.459	.458	.473	.459
<i>Panel B: Δ GOP vote share</i>															
Retaliation exposure	0.750*** (0.054)	0.144*** (0.029)	0.222*** (0.033)	0.891*** (0.057)	0.203*** (0.026)	0.277*** (0.040)	2.598*** (0.368)	0.383** (0.168)	0.038 (0.227)	0.880*** (0.239)	-0.062 (0.096)	0.218* (0.116)	2.885*** (0.833)	-0.013 (0.312)	1.191*** (0.264)
Observations	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063
States	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063	3063
Mean of DV	-0.0137	.0145	-0.0522	-0.0137	.0145	-0.0522	-0.0137	.0145	-0.0522	-0.0137	.0145	-0.0522	-0.0137	.0145	-0.0522
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in Panel A or the change in republican party vote share between consecutive presidential elections in Panel B. The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. All regressions include state fixed effects. Counties are weighted by their population. Standard errors are clustered at the state level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Robustness of degree of political targeting of retaliation: inclusion of additional county-level controls

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: 2016 GOP vote share</i>						
Retaliation exposure	2.459*** (0.233)	2.436*** (0.236)	2.414*** (0.256)	2.154*** (0.252)	1.893*** (0.201)	2.009*** (0.209)
R2	.451	.457	.459	.504	.609	.631
Observations	3104	3104	3104	3104	3104	3056
<i>Panel B: Δ GOP vote share 2016-2012</i>						
Retaliation exposure	0.750*** (0.054)	0.743*** (0.054)	0.741*** (0.056)	0.695*** (0.057)	0.581*** (0.049)	0.478*** (0.045)
R2	.598	.605	.613	.625	.698	.744
Observations	3063	3063	3063	3063	3063	3056
State FE	Yes	Yes	Yes	Yes	Yes	Yes
ADH China Shock	No	Yes	Yes	Yes	Yes	Yes
Agricultural Sectors	No	No	Yes	Yes	Yes	Yes
Mining Sectors	No	No	No	Yes	Yes	Yes
Manufacturing Sectors	No	No	No	No	Yes	Yes
Turnout	No	No	No	No	No	Yes

Notes: The dependent variable is either the republican vote share in the 2016 Presidential election at the county level in Panel A or the change in republican party vote share between the 2016 and 2012 Presidential elections in Panel B. The retaliation exposure measure combines the measures for Canada, Mexico, China and the EU. The "Sectors" variables include 3-digit sector county-level employment share covering 31 sectors in total. Counties are weighted by the county-level population. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Retaliation exposure and Presidential election turnout

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: Presidential Election Turnout</i>					
Retaliation exposure	-0.497*** (0.065)	-0.530*** (0.075)	-1.817*** (0.508)	-0.921*** (0.297)	-2.546*** (0.907)
Observations	3100	3100	3100	3100	3100
Clusters	3100	3100	3100	3100	3100
Mean of DV	.603	.603	.603	.603	.603
	Combined	Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel B: Δ Presidential Election Turnout 2016-2012</i>					
Retaliation exposure	-0.109*** (0.023)	-0.131*** (0.027)	-0.056 (0.193)	-0.134* (0.071)	-0.483** (0.196)
Observations	3056	3056	3056	3056	3056
Clusters	3056	3056	3056	3056	3056
Mean of DV	.0362	.0362	.0362	.0362	.0362
State FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A or the change in republican party vote share between 2016 and 2012 in Panel B. All regressions include state fixed effects. Counties are weighted by the county-level population. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Matching Estimates Continuous

	(1)	(2)	(3)	(4)	(5)
<i>Panel A: 2016 GOP vote share</i>					
Retaliation exposure	0.412*** (0.072)	0.495*** (0.071)	0.507*** (0.074)	0.489*** (0.074)	0.522*** (0.073)
Observations	1552	1552	1552	1552	1552
<i>Panel B: Δ GOP vote share 2016-2012</i>					
Retaliation exposure	0.122*** (0.024)	0.134*** (0.025)	0.156*** (0.025)	0.151*** (0.025)	0.149*** (0.025)
Observations	1552	1552	1552	1552	1552
State FE	Yes	Yes	Yes	Yes	Yes
Propensity score difference	Yes	Yes	Yes	Yes	Yes
Matched on:					
Baseline	Yes	Yes	Yes	Yes	Yes
Occupational structure		Yes	Yes	Yes	Yes
3-digit NAICS shares			Yes	Yes	Yes
Poverty				Yes	Yes
Ethnic					Yes

Notes: The table presents results from a matching exercise. Counties are divided into top-quartile versus lower quartiles exposure of the combined retaliation exposure measure. For each county in the top quartile, a matched county is identified that is in a lower quartile that is similar on observables using a successively larger set of measures. We control for state fixed effects and the quintile of the propensity score difference between matched counties. The variables used to construct matched pairs are as follows. Baseline controls include the Republican presidential vote share in 2012, total population, the number of export dependent jobs, the ADH China shock and median earnings. Occupations controls are the share of people working in management, service, sales, farming construction and production occupations. NAICS controls control for 3-digit NAICS industry county-level employment shares from the CBP measured in 2016. Poverty controls include unemployment and the share of people below the poverty threshold. Ethnicity includes the share of the population that is White, African-American, Native American, Asian American, Latino or Other Races. Standard errors are clustered at the county level presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Matching Estimates Dummified

	(1)	(2)	(3)	(4)	(5)
<i>Panel A: 2016 GOP vote share</i>					
Retaliation exposure (dummified)	0.030*** (0.007)	0.037*** (0.007)	0.033*** (0.006)	0.031*** (0.006)	0.034*** (0.006)
Observations	1552	1552	1552	1552	1552
<i>Panel B: Δ GOP vote share 2016-2012</i>					
Retaliation exposure (dummified)	0.011*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.012*** (0.002)
Observations	1552	1552	1552	1552	1552
State FE	Yes	Yes	Yes	Yes	Yes
Propensity score difference	Yes	Yes	Yes	Yes	Yes
Matched on:					
Baseline	Yes	Yes	Yes	Yes	Yes
Occupational structure		Yes	Yes	Yes	Yes
3-digit NAICS shares			Yes	Yes	Yes
Poverty				Yes	Yes
Ethnic					Yes

Notes: The table presents results from a matching exercise. Counties are divided into top-quartile versus lower quartiles exposure of the combined retaliation exposure measure. For each county in the top quartile, a matched county is identified that is in a lower quartile that is similar on observables using a successively larger set of measures. We control for state fixed effects and the quintile of the propensity score difference between matched counties. The variables used to construct matched pairs are as follows. Baseline controls include the Republican presidential vote share in 2012, total population, the number of export dependent jobs, the ADH China shock and median earnings. Occupations controls are the share of people working in management, service, sales, farming construction and production occupations. NAICS controls control for 3-digit NAICS industry county-level employment shares from the CBP measured in 2016. Poverty controls include unemployment and the share of people below the poverty threshold. Ethnicity includes the share of the population that is White, African-American, Native American, Asian American, Latino or Other Races. Standard errors are clustered at the county level presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Measuring degree of political targeting of retaliation: individual-level quasi panel data

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: Voted for Trump in 2016</i>					
Retaliation exposure	0.905*** (0.118)	1.190*** (0.131)	2.520*** (0.696)	0.766** (0.382)	2.813** (1.406)
Observations	44920	44920	44920	44920	44920
Counties	2506	2506	2506	2506	2506
Mean of DV	.46	.46	.46	.46	.46
<i>Panel B: All switchers 2012-2016</i>					
Retaliation exposure	0.518*** (0.106)	0.744*** (0.143)	1.572** (0.675)	0.221 (0.246)	1.006 (0.810)
Observations	39465	39465	39465	39465	39465
Counties	2418	2418	2418	2418	2418
Mean of DV	.0221	.0221	.0221	.0221	.0221
<i>Panel C: Switched to Trump from Obama</i>					
Retaliation exposure	0.334*** (0.079)	0.483*** (0.116)	0.954** (0.453)	0.120 (0.157)	0.816 (0.531)
Observations	39465	39465	39465	39465	39465
Counties	2418	2418	2418	2418	2418
Mean of DV	.0706	.0706	.0706	.0706	.0706
State FE	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Republican Party Affiliation	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy indicated in the panel label. All regressions control for state FE and are weighted with the provided survey weights. Regressions include individual level controls: respondents racial identity, income, republican party affiliation and gender. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Focusing on actual validated voters: Measuring degree of political targeting of retaliation individual-level quasi panel data

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: Voted for Trump in 2016</i>					
Retaliation exposure	0.961*** (0.133)	1.253*** (0.145)	2.395*** (0.825)	0.879* (0.453)	3.231** (1.632)
Observations	31172	31172	31172	31172	31172
Counties	2337	2337	2337	2337	2337
Mean of DV	.465	.465	.465	.465	.465
<i>Panel B: All switchers 2012-2016</i>					
Retaliation exposure	0.635*** (0.119)	0.896*** (0.157)	1.660* (0.892)	0.375 (0.298)	1.188 (0.911)
Observations	27958	27958	27958	27958	27958
Counties	2263	2263	2263	2263	2263
Mean of DV	.0133	.0133	.0133	.0133	.0133
<i>Panel C: Switched to Trump from Romney</i>					
Retaliation exposure	0.420*** (0.086)	0.592*** (0.128)	1.166** (0.545)	0.215 (0.169)	0.664 (0.532)
Observations	27958	27958	27958	27958	27958
Counties	2263	2263	2263	2263	2263
Mean of DV	.0614	.0614	.0614	.0614	.0614
State FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy indicated in the panel label. All regressions control for state FE and are weighted with the provided survey weights. Standard errors are clustered at the county level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2 What are the economic effects of retaliation?

As a first measure of economic impact, we study the effects of retaliation on trade flows and export price indices. While reduced trade-flows could purely capture both trade-disruptions as well as trade-diversion, any impact of retaliatory tariffs on export price indices is likely to indicate tangible economic shocks.

2.1 Data on Economic Impact Measures

To quantify the economic impact of the trade retaliation measures on trade flows, we construct a dataset capturing monthly US trade flows, particularly exports at the 10 digit HS code level mapping the level at which retaliation was issued.¹ Similarly, we collected additional data capturing Export Price Indices developed by the Bureau of Labor Statistics, which are released on a monthly basis. This data is available for around 90 different four digit NAICS sectors and will help complement the analysis on trade flows. Specifically, since trade flows may simply be re-routed, it could be that the income implications of the tariff may be limited. Hence, studying export price indices may help shed light on whether tariffs actually did produce a negative income shock.

2.2 Empirical specification

Impact on exports We first investigate the impact of retaliation on US trade flows. We use monthly US export data at the HS8 level to measure US exports to China, the EU, Canada and Mexico as well as the rest of the world. We then estimate the following difference-in-difference regression:

$$y_{r,h,t} = \alpha_{r,h} + v_{i,t} + \beta_r \times \text{Post July 2018} \times T_{h,r} + \epsilon_{h_4} \quad (1)$$

¹These data can be found here <https://usatrade.census.gov/>.

In this specification y measures US exports and the index r indicates the country which retaliated against the US. $T_{h,r}$ is indicator variable which is 1 if good h was chosen to be included in the retaliation basket of country r . The regressions control for a range of shifters and fixed effects. Most importantly we include HS8 by trading country specific shifters $\alpha_{c,h}$ capturing country r specific tastes for imports from the US of goods h . We also control for destination country r specific time fixed effects as well as additional time fixed effects, indicated here by $v_{i,t}$. These additional time effects can be specific to a destination country r or, could account for good-specific seasonality. The latter is particularly relevant as US agricultural exports are highly seasonal.

Impact on export prices Secondly, we estimate the impact of retaliation on export price indices. This analysis is based on export price indices constructed for 46 NAICS4 sectors by the Bureau of Labor Statistics. We study to what extent sectors more exposed to retaliation measures saw a differential change in their export prices. To do so, we construct the exposure of a NAICS4 sector n to retaliation from country r , indicated as $E_{n,r}$ as follows. Having merged the HS8 export data to NAICS codes, we compute the total volume of US exports in 2017 at the 4 digit NAICS level that would become subject to retaliatory tariffs from July 2018 by country r and divide this by the overall export volume. The tariff exposure measure across the 46 four digit industry groups for which it is constructed ranges from 0 to 34.6%, indicating that at the top 34.6% of exports produced by an industry was affected by tariffs. The average exposure measure is 5%. We then estimate the following regression:

$$y_{n,t} = \alpha_{n_j} + v_{i,t} + \beta_r \times \text{Post July 2018} \times E_{n,r} + \epsilon_{n,t} \quad (2)$$

The dependent variable measures the export price index at the four digit NAICS sector n . The sector fixed effects, α_{n_j} , are at the level of the three digit sector or the four digit sector. Hence, we explore both within and between NAICS sector variation. We include time fixed effects throughout. Further, in some more demanding specifications we allow for time by first digit NAICS sector fixed effects. These first digit sectors broadly distinguish agriculture, mining and manufacturing. Standard errors are clustered at the four digit NAICS sector level. The main coefficient of interest is β_r . We would expect that this coefficient to be negative, indicating that after retaliatory measures came into effect, export price indices decrease for exports from sectors with a higher retaliation exposure $E_{n,r}$.

2.3 Results

Impact on exports The regression results are presented in Table B1. The point estimates in panel A suggest that exports that were exposed to retaliation shrank by around 75%. Panel B-E explores to what extent this result is robust to the exclusion of specific trading partner. It becomes obvious that, the Chinese retaliation, accounts for around 50-60% of the estimated contraction of US exports. This is expected since the Chinese retaliation was by far the most extensive given the structure of US trade with China. Nonetheless, also goods targeted by the EU, Canada and Mexico exhibit a significant reduction in exports to these markets.

Overall, the point estimate suggest that each month around USD 2.55 billion worth of exports have either not taken place or were diverted as a result of the tariff measures, amounting to around USD 15.28 billion in aggregate since the retaliation measures became effective in July 2018 until the end of 2018. Panel A in Figure B1 provides an event study version of specification 1, estimating separate coefficient for each pre-and post treatment month. The figure highlights the sharp

contraction in export volumes since July 2018, when most retaliation measures became effective. In Appendix Figure B2, we estimate the event studies focusing on pairs of countries, studying the US exports to a specific country that retaliated and to the rest of the world with just these two series. The results highlight a strong degree of seasonality in exports of goods that were subject to retaliation by China, which captures the agricultural crop cycle across the US. Notably, the peak in exports that should occur around the summer failed to materialize as commodity exports fell significantly due to retaliation. The figure suggests significant contractions in bilateral exports relative to trade with the rest of the world across the dyads that were affected by the retaliatory measures.

These results do not preclude the possibility that most of this trade was rerouted and absorbed by other trading partners. Yet using the case of soybeans, a look at aggregate numbers suggests, that there is a net contraction of exports. In other words, the exports to the rest of the world have not absorbed the tariff-induced reduction in demand.

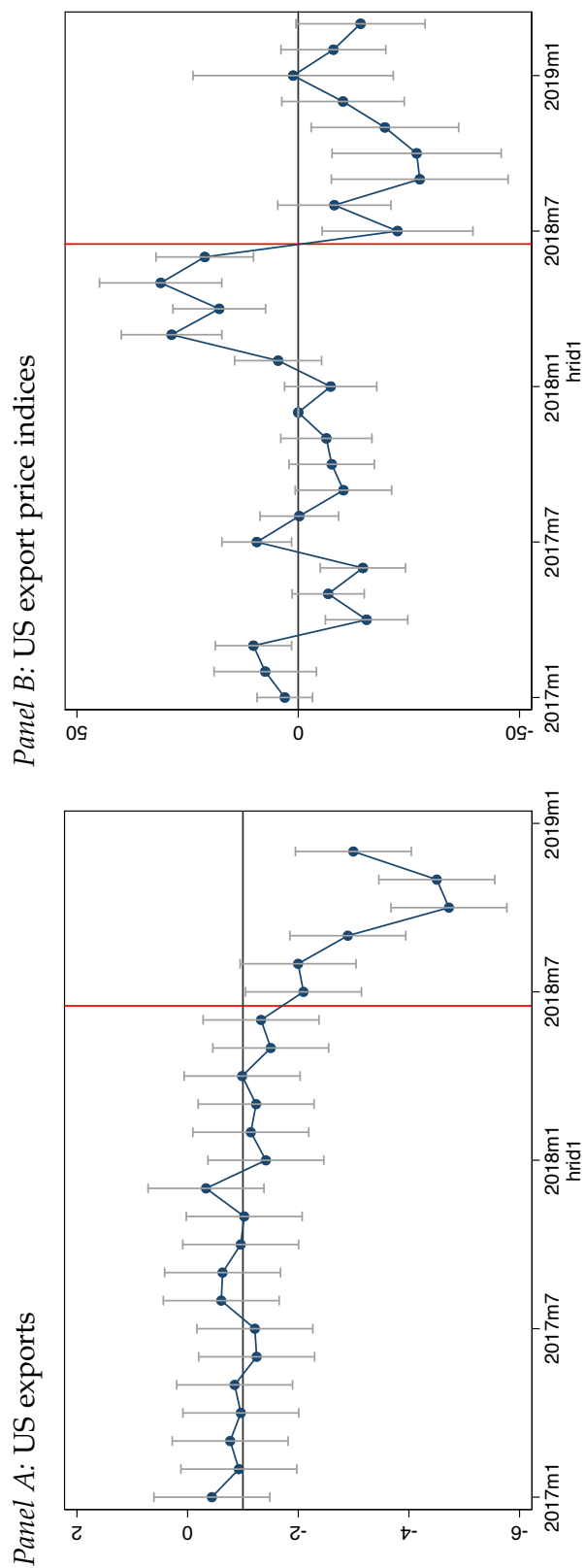
To show that the retaliatory tariffs likely also had a significant effect on incomes in areas that produce the affected commodities (and not just capture trade-rerouting), we next provide some evidence suggesting that US export price indices also significantly declined.

Impact on export prices Table B2 presents the results from this analysis. Since the data are aggregated into far coarser industry sectors, the point estimates are unsurprisingly more noisy. Nevertheless, the results suggest that export prices declined significantly in 4-digit NAICS sectors that were more exposed to retaliatory tariffs. Panel A studies the overall sector level retaliation exposure measure, while in Panels B - E, split the retaliation exposure measure by country. The findings indicate that, at the coarse four digit level, only the retaliation by China, Mexico

and Canada had a significant effect on export price indices. To reiterate, this is not surprising given the coarseness of the export price indices data. The results also rely on variation between 4 digit NAICS sectors (in columns 1-3). When we fully focus on within sector variation over time (columns 4-6), the estimates are even more noisy.

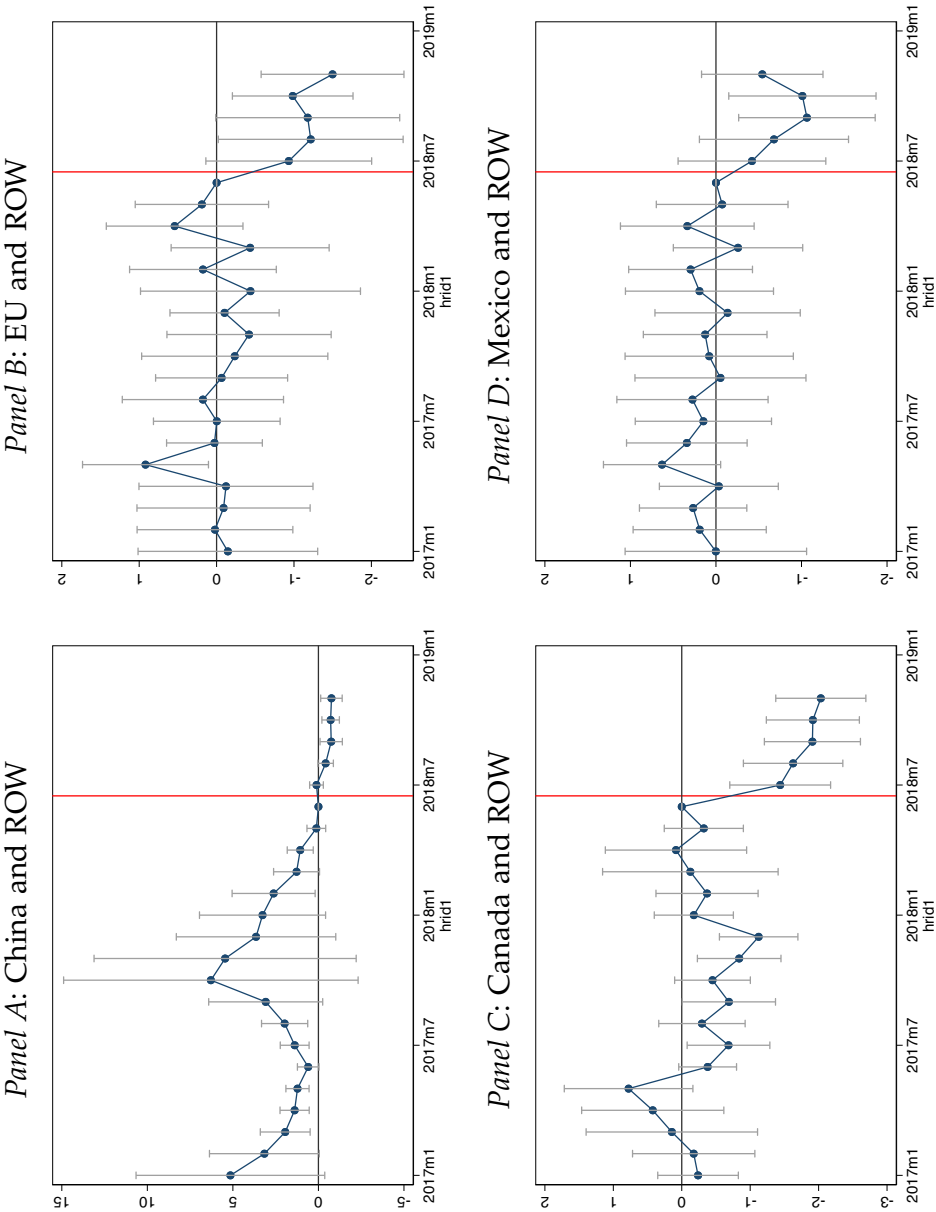
To illustrate the timing of the effects, in Panel B of Figure **B1** shows that the contraction in export price indices occurs at the time of the introduction of retaliatory measures, with export prices growing strongly in early 2018. This could partly highlight increased demand due to stockpiling. Taken together, the evidence from exports as well as exports prices, indicates that the retaliatory tariffs did indeed, induce some economic harm on the effected sectors. In that sense the tariffs were effective.

Figure B1: Did retaliation affect trade flows and export prices?



Notes: Figure plots estimates from a difference-in-difference regressions. Panel A presents point estimates capturing the evolution of exports from the US to EU, China, Canada, Mexico and the ROW over time on goods targeted by retaliation. The underlying regressions control for HS8 code by destination shifters, destination by time fixed effects and targeted sector specific seasonality. Standard errors are clustered at the 4 digit HS code level. The right Panel B presents results from a regression studying 46 export price indices constructed at four digit NAICS level. The plot presents point estimates capturing the evolution of export price indices over time as a function of the 4 digit NAICS sectors exposure to retaliation measures as the share of exports in 2017 at the NAICS4 level that was exposed to retaliation measures. The underlying regressions control for NAICS4 export price index fixed effects and time fixed effects; regressions are weighted by the 2017 overall export volume and standard errors are clustered at the NAICS4 level. 90% confidence bands are indicated.

Figure B2: Impact of retaliation on US exports to retaliating country and the Rest of the World: pairwise event studies



Notes: Figure plots estimates of the effect of retaliation exposure on trade between the US and the respective country vis-a-vis the rest of the world (not including China, Canada, Mexico and the EU). Estimates control for destination by HS8 good fixed effects and time effects. Standard errors are clustered at the HS4 level and 90% confidence bands are indicated.

Table B1: Did retaliation affect trade flows?

	(1)	(2)	(3)	(4)
<i>Panel A: Overall</i>				
Post July 2018 × Targeted	-2.729** (1.102)	-2.511** (1.064)	-3.124* (1.611)	-2.305 (1.586)
Observations	1726560	1726560	1726560	1726560
Clusters	1231	1231	1231	1231
Mean of DV	3.57	3.57	3.57	3.57
<i>Panel B: Excluding China</i>				
Post July 2018 × Targeted	-1.136*** (0.239)	-0.970*** (0.205)	-0.813*** (0.147)	-0.900*** (0.169)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	4.11	4.11	4.11	4.11
<i>Panel C: Excluding EU</i>				
Post July 2018 × Targeted	-3.113** (1.341)	-2.851** (1.305)	-3.584* (1.926)	-2.527 (1.870)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	3.63	3.63	3.63	3.63
<i>Panel D: Excluding CA</i>				
Post July 2018 × Targeted	-3.157** (1.406)	-2.895** (1.369)	-3.793* (2.074)	-2.729 (2.042)
Observations	1381248	1381248	1381248	1381248
Clusters	1231	1231	1231	1231
Mean of DV	3.65	3.65	3.65	3.65
<i>Panel E: Excluding MX</i>				
Post July 2018 × Targeted	-2.818** (1.166)	-2.580** (1.125)	-3.225* (1.659)	-2.362 (1.613)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	3.75	3.75	3.75	3.75
HS8 × Dest FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No
Destination × Time FE	No	Yes	Yes	Yes
Targeted goods × Seasonality	No	No	Yes	Yes
HS8 × Dest Linear trends	No	No	No	Yes

Notes: The dependent variable is the level of US exports at the HS8 level by month. Standard errors are clustered at the 4-digit HS good level with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Did retaliation affect export price indices?

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Overall</i>						
Post July 2018 \times Tariff exposure	-76.960* (43.800)	-138.614* (73.133)	-117.954* (69.375)	-18.706** (8.084)	-7.911 (18.056)	-29.731*** (7.853)
Observations	1568	1529	1568	1568	1529	1568
Clusters	42	41	42	42	41	42
Mean of DV	114	114	114	114	114	114
<i>Panel B: Focusing on China</i>						
Post July 2018 \times Tariff exposure	-17.667** (8.542)	-74.786** (33.738)	-31.774 (19.728)	-9.516*** (1.517)	-14.848 (10.860)	-13.024*** (1.156)
Observations	1568	1529	1568	1568	1529	1568
Clusters	42	41	42	42	41	42
Mean of DV	121	122	121	121	122	121
<i>Panel C: Focusing on EU</i>						
Post July 2018 \times Tariff exposure	-1.075 (15.478)	-1.249 (15.594)	-4.752 (22.257)	-0.365 (6.335)	-0.496 (6.422)	0.829 (4.132)
Observations	1568	1529	1568	1568	1529	1568
Clusters	42	41	42	42	41	42
Mean of DV	113	113	113	113	113	113
<i>Panel D: Focusing on CA</i>						
Post July 2018 \times Tariff exposure	-56.347*** (14.394)	-56.893*** (14.635)	-71.783*** (16.744)	5.837 (4.627)	5.387 (4.641)	1.804 (5.412)
Observations	1568	1529	1568	1568	1529	1568
Clusters	42	41	42	42	41	42
Mean of DV	111	111	111	111	111	111
<i>Panel E: Focusing on MX</i>						
Post July 2018 \times Tariff exposure	-87.004* (45.284)	-87.592* (48.127)	-98.203** (43.622)	-9.662 (13.258)	-4.686 (11.914)	-43.422 (31.265)
Observations	1568	1529	1568	1568	1529	1568
Clusters	42	41	42	42	41	42
Mean of DV	110	110	110	110	110	110
Base Fixed effects	NAICS3	NAICS3	NAICS3	NAICS4	NAICS4	NAICS4
NAICS1 \times Time FE	No	Yes	No	No	Yes	No
Linear Time trend	No	No	NAICS3	No	No	NAICS4

Notes: All regressions include time fixed effects. The dependent variable is the 4 digit NAICS sector level export price index constructed by the Bureau of Labor Statistics. The tariff-exposure measures the share of 4-digit NAICS sector exports measured in 2017 affected by retaliation. In Panel B- E, the retaliation exposure measure is constructed focusing solely on the respective trading block. Regressions are weighted by the overall level of exports in 2017 at the 4-digit NAICS level. Standard errors are clustered at the 4-digit NAICS sector with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.